INTEGRATED DETERMINISTIC / PROBABILISTIC PETROLEUM VOLUME EVALUATION FOR A CARBONATE RESERVOIR

BY

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This thesis, written by **Sami Hamad Saleh Al-Shridi** under the direction of his thesis advisor and approved by his thesis committee, has been presented to and accepted by the Dean of Graduate Studies, in partial fulfillment of the requirements for the degree of **MASTER OF SCIENCE IN GEOLOGY**.

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Dedication

I would like to dedicate my thesis to my wife and children for their patience, support, and their moral encouragement during the study and thesis work.

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THESIS ABSTRACT

Name: Sami Hamad Saleh Al-Shridi
Title: Integrated Deterministic / Probabilistic Petroleum Volume Evaluation for a Carbonate Reservoir
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For an oil company, it is most important to estimate hydrocarbon volumes accurately so that development and production plans can be prepared. There is always uncertainty in hydrocarbon volume estimates. Main factors that affect hydrocarbon volume uncertainty are geological, geophysical and petrophysical. Better data quality using advanced technology and interpreter's experience in choosing representative parameters may reduce such uncertainty. Still uncertainty in hydrocarbon volume is dependent on quality and quantity of data, reservoir complexity, and methodology used in the calculations.

The objective of this thesis is to add value of integrating deterministic and probabilistic methods to quantify uncertainty and to identify additional potential in hydrocarbon volume estimates. The quantified uncertainty and risk in hydrocarbon volume estimates are used to make economical decisions in exploration, delineation and field development. Probabilistic methodology is an important tool to quantify parameters involved in hydrocarbon volume estimates. A single deterministic hydrocarbon volume number does not show uncertainty or any hydrocarbon potential.

In this study, two strategies were used in pore-volume evaluation. In one case, the reservoir was subdivided into three zones and their average properties were determined. Their pore-volume distributions for each zone were simulated individually and then aggregated by using Monte Carlo simulation. In second case no zonation was done and average properties were determined. The pore-volume distribution was simulated for the whole reservoir. In both simulations cases, three distribution functions are used as inputs: Net pay, Porosity, and Area. Parameters in a model can be either "independent" or "dependent" and both cases were assumed in this study.

The result of this study showed that applying aggregation and dependency lead to better results by having additional pore volume and quantify parameters uncertainties. This is due to honoring the individual zone distributions. In the correlated case, simulation resulted in a tighter hydrocarbon volume distribution (smaller standard deviation). Hydrocarbon volumes calculated in both cases were significantly different. Integrated deterministic-probabilistic methods were used to calculate hydrocarbon volume (oil in-place, oil reserves) with improved overall model accuracy. Monte Carlo simulations produced good hydrocarbon volume estimates despite the uncertainty in basic parameters. This methodology yields a product that helps define the risks and uncertainties inherent in hydrocarbon volume estimations.

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ملخص الرسالة

الاسم : سامي حمد صالح الشريدي
العنوان : تكامل المعلومات التحديديه والتقديرات الإحتمالية للزيت في مكمن
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يعتبر فهم تّوزيع خصائص المكمن مثل نوعية الصخور ومساميتها و تقديرات الزيت الصحيحة مهمة أساسيةُ لتَطوّر الحقول النفطية و الإنتاج للمكمن. البيانات تَجيء من مصادر متعدّدة وفي وحدات قياس مختلفة و بدرجات ثقة متفاوتة. هناك عناصر رئيسية تؤثر في عملية الشك في تحديد كمية الزيت بدقه للمكمن مثل الجيولوجية و الجيوفيزيائية والصخرفيزيائية لذالك وجب استخدام التكنولوجيا المتقدمة لتقليل نسبة الشك الجيولوجية. الجيولوجيا الإحصائية تساعد الجيولوجيين ومهندسي البترول في تَحليل بيانات مختلفة و دمجها ومن ثم استخدمها في إنتاج نتائج ذات دقة عالية. في هذه الدراسة طبقت طريقة تكامل تقديرات الزيت الاحتماليه والتحديديه على منطقه مستقطعه لمكمن نفطي.

هدف هذه الرسالة أن تقيم إضافة أنواع البيانات من مصادر مختلفة لمكاملة المعلومات المحددة و تقديرات الزيت الاحتماليه لتقيم إنخفاض مقدار الشك في النماذج الجيولوجية المحتملة للمكمن .إن تقيم الشك في كمية الزيت يؤدي إلى إتخاذ قرارات إقتصادية مهمة في تنقيب و تطوير مكامن النفط. لإنجاز هذا الهدف استراتيجيتين قّد بنِيت بطرق مختلفة. النموذج الأول قّد بني معتمدا على تقسيم المكمن إلى ثلاث مجموعات وتم تقيم كل مجموعة على حده . أما النموذج الثاني بني معتمدا على اتخاذ المكمن كمجموعة واحده. وقد تم تقيم هذه النّماذج بمزج معلومات الجيولوجية والصخرفيزيائية باستعمال طرق نوعية وكمّية لمونتي كارلو المتعددة. مع مراعاة استخدام العلاقة المتباينة في خصائص المكمن وعدم استخدامها في الحالتين من اجل حصر نماذج واقعية لجيولوجيا المكمن ولضمان إحترام العلاقات البينية المتداخلة للخصائص.

أظهرت هذه الدّراسة إن حسابات النماذج المسامية التي بنيت على معلومات جيولوجية لنظام المكمن المجزأ إلى ثلاث مجموعات مع مراعاة استخدام العلاقة المتباينة في خصائص المكمن كَانت أفضل من النّموذج الأخر من حيث الدقة وكمية الزيت. هذه بسبب أن المعلومات ذات كفائه عالية. تم حساب المخزون النفطي المعدل في كل مجموعة, ثم طبقت عمليات حساب إحصائية وعمل وسائل إحصائية توضيحية على كمية النفط

المحسوبة في كل مجموعة على حده. لقد وجد في هذا البحث إن مقدار الشك قد حصر في مستويات متدنية عند مكاملة المعلومات. هذا يوضح أهمية استعمال جميع البينات المتوفرة في حسابات النماذج المسامية للنفط.

درجة الماجستير في العلوم
جامعة الملك فهد للبترول والمعادن
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CHAPTER 1

INTRODUCTION

Pore-volume estimation of a hydrocarbon reservoir is the most essential data for oil company development and production planning. Since scientists can never fully understand the subsurface, then the volume estimation is always subject to uncertainty. Primary controls on uncertainty are geological, geophysical, and petrophysical. Technology and experience can help in reducing uncertainty. However, estimation reliability is directly related to data quality and quantity, complexity of the reservoir, and the applied methodology.

Hydrocarbon pore-volume is estimated by using either deterministic or probabilistic methods. Deterministic pore-volume estimation is single point value, while probabilistic determination generates a distribution of possible pore-volume outcomes. The calculation of hydrocarbon pore-volume of a reservoir rock does not yield an exact answer. The accuracy of each parameter used in the calculation depends on the precision of measurement (Murtha, 1995).

The quantification and classification of estimates of hydrocarbon reserves and pore-volume are subjective processes. Estimates of pore-volume are developed under conditions of uncertainty, and their reliability and classification are related to the quality of available data. Geological data used for pore-volume estimation include well logs, formation tops, seismic maps, core analysis, and reservoir characteristic analyses (PSCIM, 1994).

In the petroleum industry many factors influence pore-volume and reserves estimations. These factors include economics and software related to technology, and geology. By studying pore-volume estimation procedures the uncertainty in these factors can be minimized. Petroleum reservoirs are heterogeneous, so the value of each parameter varies from sample to sample. Performing statistical techniques is one method of handling the variations. Statistical methods quantify the uncertainty by defining the range of probable values within the much larger range of possible values (Mata et al, 1997).

There are many variables that affect the estimation of pore-volume and reserves regardless of whether deterministic or probabilistic methods are used. Among them are the areal extent of accumulation, pay thickness, and porosity.

1.1 Objectives

The objective of this research is to assess the utility of probabilistic methodology as an aid in quantifying uncertainty and in pore-volume estimation. Integrating the deterministic and probabilistic estimations yield a better result. Indeed, this will help in decision-making in exploration, drilling planning, field development, production planning, and economic evaluation.

To achieve this objective, hydrocarbon pore-volume initially is mapped using deterministic methods. The deterministic work provides the basis for probabilistic pore-volume estimations. Monte Carlo simulation is performed to generate a reservoir pore-volume distribution. The generated distributions describe the range of possible pore-volumes and the probabilities of achieving a particular estimate. The outcome of this methodology helps in defining the risk and uncertainties inherent in hydrocarbon pore-volume estimations.

1.2 Dataset Description

An area relevant to the Arab-D Reservoir of an onshore field has been selected as a study area for this project. The Arab-D Formation is part of the Upper Jurassic section in Saudi Arabia. The study area has 19 vertical wells drilled in the Arab-D Reservoir. All wells have porosity logs derived from sonic, neutron, and density logs. Seven wells have been cored and described by Saudi Aramco geologists.

The Arab-D reservoir is a carbonate reservoir of Upper Jurassic, Kimmeridgian in age. Its environment of deposition ranges from relatively shallow subtidal to supratidal. The Arab-D reservoir is composed of limestone, dolomite and anhydrite (Saudi Aramco, 1985).

1.3 Methodology

The statistical distributions of porosity from logs and core data are studied first. Then the distributions are used to establish a relationship between porosity logs (i. e. derived from sonic, neutron, density logs) and core data. Other variables that affect the estimation of pore-volume and reserves such as area, pay thickness, and hydrocarbon saturation, are also subject to statistical analysis.

Deterministic pore-volume estimations are single point values. A volumetric calculation of hydrocarbon resources is an estimation of the volume of subsurface rock that contains oil or gas. The volume is derived from the thickness of the reservoir rock that contains oil or gas and the areal extent of the accumulation.

Mapping of the hydrocarbon reservoir is the most important step in volumetric estimation. Cross sections and diagrams are required to understand the reservoir geometry. Maps including structural maps, isopach maps, and porosity-thickness maps are prepared in a logical sequence. The maps sets integrate the results of core data, well log calculations, seismic data, and well test data.

The first step in the probabilistic approach is to assess risk by identifying the project variables. Such variables have large ranges and critical impact on the pore-volume. A probability distribution is selected to model each critical variable. Once the probability distribution is defined, then the range of the critical variables is determined.

The second step of the probabilistic analysis is to conduct Monte Carlo simulation analysis. Monte Carlo simulation uses the selected frequency distributions of the identified project variables to perform random selections in each trial.

The third and final step of the probabilistic method analysis is interpretation. It relies on graphical tools such as histograms of the relative frequency, and the cumulative frequency for each variable generated from the Monte Carlo simulation.

1.4 Facilities

Saudi Aramco provided all data needed (i.e. well logs and lithology description) for conducting this research. Geolog, StratWorks, and Monte Carlo simulation software are used in this study.

The work is carried out using Unix based Silicon Graphics Octane workstation dual screen with 250 MHz IP30 processor, memory size of 1536 Mbytes and hard disk size of 13 Gbytes.

CHAPTER 2

LITERATURE REVIEW

2.1 Pore-volume Determination

The Original Hydrocarbon quantity in place is one of the most important parameters of an oil field. The basic procedure for determining the hydrocarbon in place is the volumetric method which is geologically based calculation. The traditional volumetric methodologies for computing the hydrocarbon pore-volume is discussed both on deterministic and probabilistic bases.

2.1.1 Deterministic Overview

A deterministic estimate of the hydrocarbon volume is obtained from geological and petrophysical parameters. The deterministic evaluation is the technique that has been applied for the computation of the hydrocarbon volume since the beginning of oil industry. In this methodology, the various input parameters are calculated deterministically and no allowance is given for any related uncertainty. In other words, the distributions of the geological parameters are considered free of error, even if this is obviously not true.

The process of estimating pore-volume is characterized by the presence of uncertainties, which are related to errors in the estimations, lack of representative data, and interpretation problems. If uncertainty is ignored then the resulting deterministic estimates would be severely biased with just one possible outcome for the pore-volume. Geoscientists have always found it easier to search for one single value of pore-volume, possibly because this represents a simpler and easier approach. On the other hand, a probabilistic approach to the evaluation of the hydrocarbon reserves provides a much closer insight into the uncertainty related to the estimation process, as well as a good feeling for the accuracy of the results (Mata et al, 1997).

The geological factors to be considered in establishing a realistic estimate of a reservoir volume include the depositional environment of the reservoir beds, the history of any structural deformation of these beds, the trapping mechanism for hydrocarbon accumulation, and the position of fluid interfaces. This requires availability of structural maps for the reservoir, determination of net pay thickness, and analysis of wireline logs to determine the porosity distribution and the limit of the fluid contacts (Ross, 1998).

2.1.2 Probabilistic Overview

In general, the probabilistic approach represents a better practice in the problem of computing the hydrocarbon pore-volume. The basic idea behind probabilistic computation is to take into account the uncertainties related to the various parameters involved in the computation. The Monte Carlo approach treats the variables in a probabilistic way, by assigning them distribution functions, rather than a single, deterministic value. The procedure is illustrated in figure 2.1. It should be noted that the assessment of uncertainty related to the estimated value of the hydrocarbon pore-volume would give the geoscientists a better sense of the possible sources of inconsistencies that may arise (Cosentino, 2001).

The probabilistic approach quantifies the uncertainty in the resource estimate by using the range of values for each variable, and producing relative frequency curves to describe the probability of the values occurring within that range. This requires a determination of an appropriate distribution for each variable. Field-size distributions, pay thickness, and recovery per acre are among the various variables that have been probabilistically modeled.

Historically, a significant limitation for the application of probabilistic techniques in gas and oil exploration activities has been the lack of computer software to perform Monte Carlo simulations. Since the early 1990s, this limitation has been largely reduced by the availability of numerous programs that perform probabilistic analysis on a variety of platforms (Grace, 1997).

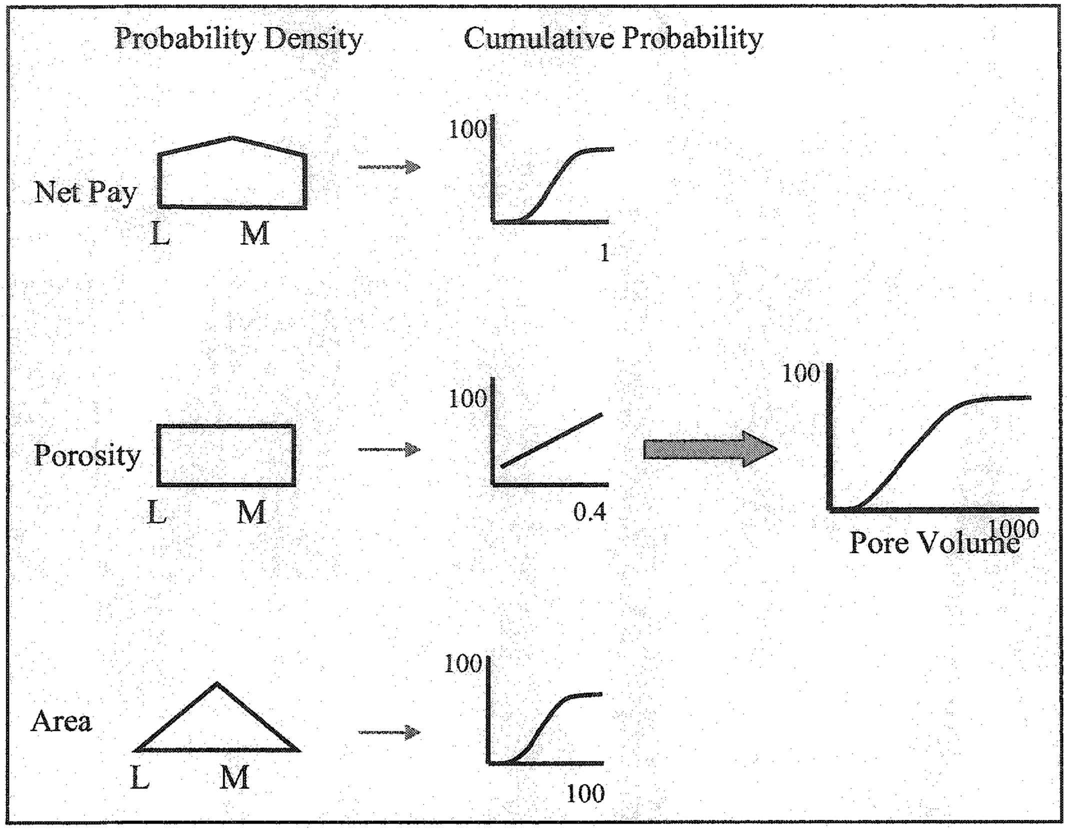


Figure 2.1: Diagram showing Monte Carlo Method, after Cosentino, 2001.

2.2 Volumetric Estimate

For a given reservoir, the determination of the hydrocarbon volume is straightforward. The reservoir is described by means of maps (or 3D grids) of the relevant geological parameters. The resulting map represents the theoretical hydrocarbon porosity-thickness values throughout the reservoir. This map provides an image of the spatial distribution of the hydrocarbons, and its mathematical completion will generate the total pore-volume (Cosentino, 2001).

2.2.1 Pore-volume - Volumetric Calculation

The volumetric calculation of the hydrocarbon requires a determination of the area and thickness of the rock containing hydrocarbons. In practice, an isopach map of net pay is planimetered to determine bulk rock volume and the average effective porosity is used to estimate pore-volume. The pore-volume equation is expressed as

$$V_p = H\ \phi\ A\ 10^4 \qquad \text{Eq.1}$$

where, V_p = pore-volume (m^3), A H represents the total volume of the reservoir. A is the drainage area in hectares (1 ha = 10^4 m^2) of well, H (meter) is the pay thickness at the wellbore. ϕ is an estimate of the fraction of the average porosity occupied by oil in the reservoir (PSCIM, 1994).

In Imperial units, the equation is as follows:

$$V_p = 7758\ H\ \phi\ A \qquad \text{Eq.1.1}$$

where, V_p is pore-volume converted to standard oil field units of acre-feet when multiplied by the constant 7758. A is the drainage area of the well; (in acres) H (feet) is the pay thickness at the wellbore (PSCIM, 1994).

The volumetric method is the only method available to the evaluator in the early stage of the reservoir's productive life. After several wells have been drilled into a reservoir, a contour map, with lines of constant pay thickness in the reservoir can be prepared. Thereafter, the map can be utilized to determine the total reservoir volume of hydrocarbon (A H) enclosed within the contours (CAPPA, 1999).

Computation of Areas and Volumes

Computing areas and volumes from either reservoir thickness or structure depth maps can be done by hand or a computer. The area of each contour is computed using numerical integration (by Trapezoid Rule) of the defining coordinate pairs of the contour. The volume is computed by a software program called Planimeter (Walsh et al, 1992). Several numerical integration methods are described and compared below:

1- Step – The Step function multiples the contour areas by the change in thickness, i.e.:

$$V_{step} = \sum_{i=2}^{n} A_i (h_i - h_{i-1})$$

2- Trapezoid Rule – The Trapezoid Rule averages the areas of the reservoir. A method commonly used in the oil industry because it captured all reservoir complexity by considering the average area of the reservoir.

3- Pyramid Rule – It computes the area of a pyramid (the areas within a pyramid cut by two planes with areas A_1 and A_2).

4- Combination Method (Trapezoid and Pyramid).

5- Simpson's Rule – This technique can only be used for evenly spaced contours and for an even number of contours. Mathematically it is more accurate than trapezoid integration.

6- Ratio – This method computes the volumes by the step method, but adds a term to consider the extra volume between contours.

7- 3/8 Rule –This technique is twice as accurate as Simpson's Rule and can only be used for evenly spaced contours.

8- Parabolic Fit – This method uses the area and thickness points to fit a parabola to describe the contour shape. A second-order least squares curve fit is computed through the (area, thickness) points.

By computing the volume using different techniques, users can compare the results before deciding which one is the most representative for the reservoir (Walsh et al, 1992).

Porosity

Porosity is defined as the ratio of the pore space volume to the bulk volume of reservoir rock. It is a non-dimensional parameter and expressed in fraction or percent. Porosity may be determined directly from cores, or indirectly from geophysical well logs or from seismic data. Cutting a core from the reservoir, and measuring the porosity in the laboratory determines core porosity. Log porosity measurements are done by sonic, density, or neutron logging tools in the well (PSCIM, 1994).

A general classification of the pore system is based on the genetic process responsible for the formation porosity. There are two fundamental types of porosity: primary and secondary.

Primary porosity is the original porosity preserved in the sediments after deposition, initial compaction and diagenesis. It is strongly dependent on the textural characteristics of the sediments and tends to decrease with age and depth of burial. Primary porosity will be modified at a later stage by fractures, stylolytes and joints.

Secondary porosity is related to tectonic stresses that affected the sediments after burial and/or to the circulation of underground waters. It is related to dissolution, deposition, recrystallisation, leaching and dolomitization processes that may affect the reservoir rock after deposition. It is more important in carbonate rocks than in siliciclastic sediments, due to the fragility of calcite and dolomite and their relatively high solubility. The most useful porosity classification scheme for reservoir description purposes is the one proposed by Choquette and Pray (1970). This classification distinguishes between seven types of porosity, on the basis of their origin and dimension: interparticle, intraparticle, intercrystal, moldic, fenestral, fractures and vugs (Cosentino, 2001).

Logs cannot replace cores, nor do cores replace logs. Both kinds of data are needed for any field development. The current practice in oil industry is to use porosity logs as the base for porosity modeling. The conducted research followed the current industry practice and used log porosity to generate porosity models by integrating geological and geophysical data.

Net Pay

Net pay is defined as a net of the reservoir rock that meets various quantitative cutoffs such as porosity, permeability, and water saturation. The term "net pay" is used to describe reservoir thickness and refers to the sum of the productive sections of the reservoir. Net pay is determined by the application of cutoffs, which refer to specified lower limits of core or log data (porosity, permeability, and fluid saturation) below which a formation will be unable to yield economic production. Net pay is important in determining the total amount of hydrocarbon in a reservoir.

Wireline logs of all types have been incorporated into the process of defining net pay. The selection of porosity cutoff to determine net hydrocarbon pay is best accomplished for normal oil and gas reservoirs by using core permeability-porosity cross-plots. Pay thickness is interpreted as being the length of the wellbore exposed to the hydrocarbon column. For a vertical well which completely penetrates the reservoir, and which does not encounter an oil-water contact, the net pay as used for the volumetric reserves calculation is h as shown in Figure 2.2 (CAPPA, 1999).

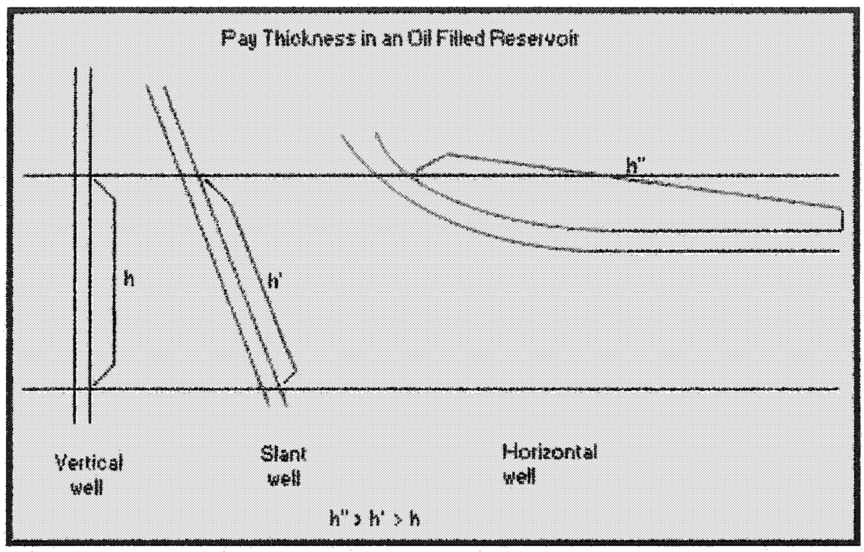


Figure 2.2: Sketch showing pay thickness in a reservoir, from CAPPA, 1999.

The cut-off is a value applied to specific reservoir parameters, in order to split the formation into pay and non-pay sections. A proper selection of the type and value of the cut-off is important for the volumetric estimates of the hydrocarbon in place. The usual approach to net pay determination is the selection of a base permeability value (1mD) and the use of a regression function to determine the corresponding porosity value. The identification of the various fluid contacts, the location of the transition zone, and the determination of other petrophysical, geological and production characteristics are essential for an accurate assessment of the net pay in the wellbore. Fluid contacts may be identified using core analysis (capillary pressure). A plot of formation pressures vs. depth can yield both formation fluid type and interface location as in figure 2.3 (Cosentino, 2001).

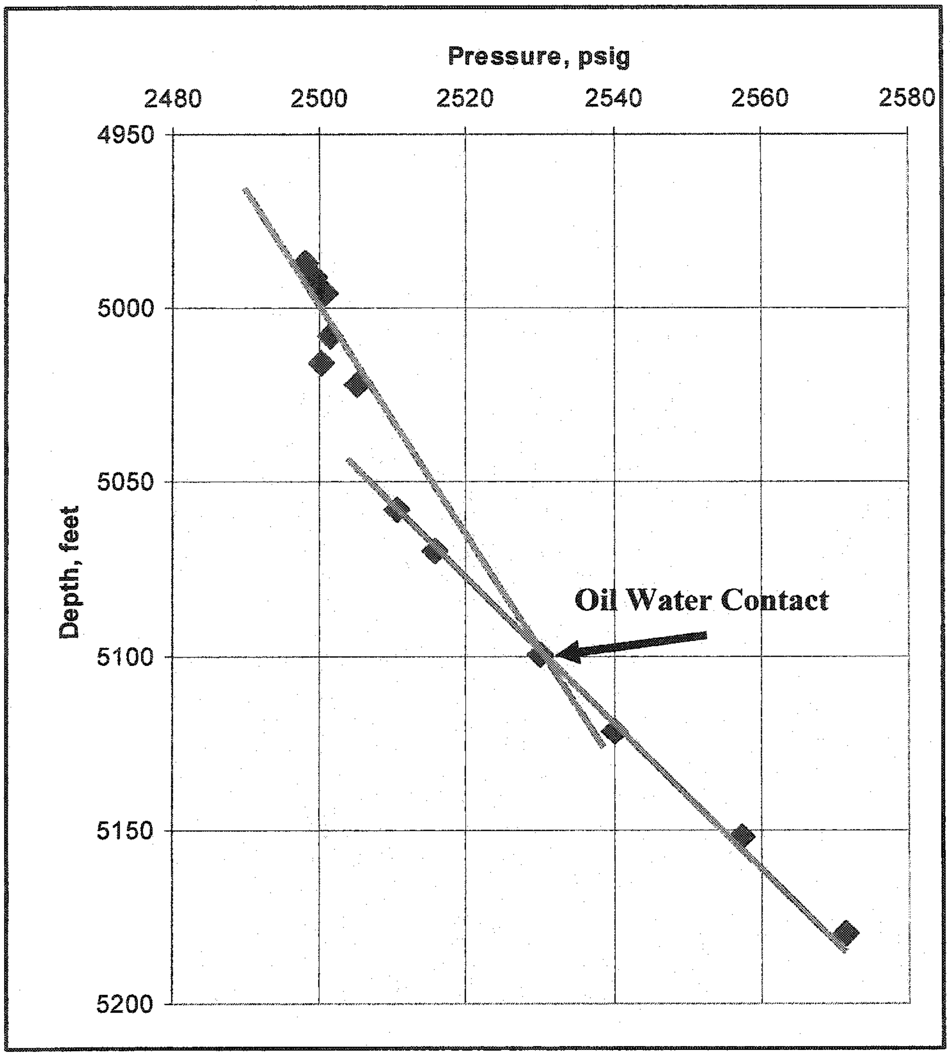


Figure 2.3: A plot of formation pressures vs. depth yields fluid types (Oil Water Contact) in green showing oil while in blue showing water, after Cosentino, 2001.

2.2.2 Risk and Uncertainty in Pore-volume

Uncertainty about a situation can often indicate a risk, which is the possibility of loss, damage, or any other undesirable event. Most people desire low risk, which would translate to a high probability of success, profit, or some other form of gain.

Volumetric uncertainty includes uncertainty about the top and bottom of the reservoir and its thickness, effective pore-volume, water saturation, and position of the fluid contacts. Significant advances have been made using seismic attributes to interpret the original oil in place. Volumetric risk is a key aspect in defining the economical aspect of the project (Larue and Friedmann, 2001).

Risk is inherent in the outcome of volumetric reservoir characterizations. The risk comes from limited information relative to the total reservoir volume and from the error in data measurements. To incorporate the risk into reservoir characterization, some qualitative aspects have modeled deterministically. Integrating geologic characteristics modeled deterministically with the probability distribution function of petrophysical attributes generates their probability distribution. Petrophysical properties are statistically analyzed to determine the best probability distribution function describing their variability. Monte Carlo simulation is one way to combine the deterministic oil volume with the petrophysical probability distribution function to generate oil volume density distribution (Holtz et al, 1997).

Estimates of pore-volume are developed under conditions of uncertainty, and their reliability and classification are directly related to the quality of data available. The uncertainty associated with any estimate of hydrocarbon volumes is handled differently in deterministic and probabilistic methods. Uncertainty in a deterministic estimate is qualitative and we must rely on judgment to express the range of possible reserve. This methodology is particularly limited in a newly discovered field, which is not well defined by geological data. Probabilistic methods use geological and engineering data to generate a range of reserve estimates with an associated probability of occurrence (Murtha, 1995).

2.3 Monte Carlo Simulation

Simulation is referred to any analytical method which tries to imitate a real-life system, especially when other analyses are too mathematically complex or difficult to carry out. Without the aid of simulation, a spreadsheet model reveals only a single outcome, generally the most likely or average scenario. Spreadsheet analysis uses both spreadsheet model and simulation to automatically analyze the effect of varying inputs on the outputs of the modeled system.

Monte Carlo simulation is an extension of deterministic modeling; however, not all simulation models are stochastic. Simulation allows judgment about the uncertainties to be incorporated into the analysis and probability distributions represent these judgments. Simulation provides a simple way to solve forecasting models where some of the input parameters are expressed as probability distributions. Among the common applications of Monte Carlo simulation are forecasting production of a well or a field, evaluation of a waterflood prospect, and estimation of hydrocarbon from a reservoir (Schuyler, 1999), as will be done in this study.

Monte Carlo Simulation is a computer-intensive technique used for assessing how a statistic performs under repeated sampling, while the response variables are simulated. A basic output is a summary of statistics describing the overall features of the simulation, as mean, standard deviation, and selected percentiles. All modules have plotting options for closer investigation of the models and for presentation of results.

In Monte Carlo methods, the computer first generates random numbers therefore it derives from the random numbers the statistical population according to the user's prescription. For each Monte Carlo iteration, the computer simulates a random sample from the population, analyzes the sample, and then stores the results. After many iterations, the stored results show the sampling distribution of the statistics. Monte Carlo technique can provide information about sampling distributions when no exact theory for the sampling distribution is available (Murtha, 1994).

Monte Carlo simulation refers to a method whereby the distribution of possible outcomes is generated by letting a computer recalculate the model over and over again, each time using different randomly selected sets of values for the probability distributions in formulas. Simulation uses two distinct operations. Selecting sets of values for the probability distribution functions contained in formulas of the model and recalculating the model using the new values.

The selection of values from probability distributions is called sampling and each calculation of the model is called an iteration. Sampling is the process by which values are randomly drawn from input probability distributions. Sampling in a simulation is done repetitively, with one sample drawn every iteration from each input probability distribution. With enough iterations, the sampled values for a probability distribution become distributed in a manner which approximates the known input probability distribution. The statistics of the sampled distribution (mean, standard deviation and higher moments) approximate the true statistics input for the distribution. The graph of the sampled distribution will even look like a graph of the true input distribution (Murtha, 1994).

Accurate results for output distributions depend on a complete sampling of input distributions. The two methods of sampling are Monte Carlo sampling and Latin Hypercube sampling. Monte Carlo sampling often requires a large number of samples to approximate an input distribution, especially if the input distribution is highly skewed or has some outcomes of low probability. Latin Hypercube sampling, a new sampling technique, forces the samples drawn to correspond more closely with the input distribution and thus converges faster on the true statistics of the input distribution

Latin Hypercube sampling, which is used in this study, is a recent development in sampling technology designed to accurately recreate the input distribution through sampling in fewer iterations when compared with the Monte Carlo method. The key to Latin Hypercube sampling is stratification of the input probability distributions. Stratification divides the cumulative curve into equal intervals on the cumulative probability scale (0 to 1.0). A sample is then randomly taken from each interval or "stratification" of the input distribution. Sampling is forced to represent values in each interval, and thus, is forced to recreate the input probability distribution.

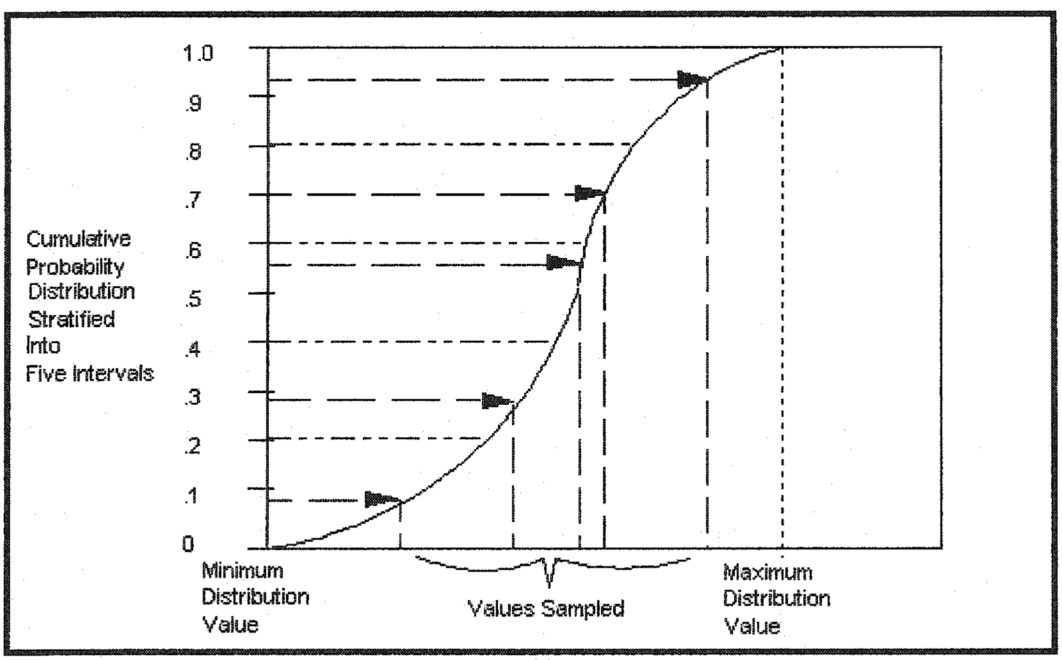


Figure 2.4: Diagram showing five iterations of Latin Hypercube Sampling (from @RISK, 2002).

In Figure 2.4 above, the cumulative curve has been divided into 5 intervals. During sampling, a sample is drawn from each interval. Compare this to the 5 clustered samples drawn using the Monte Carlo method. With Latin Hypercube, the samples more accurately reflect the distribution of values in the input probability distribution.

The technique being used during Latin Hypercube sampling is "sampling without replacement". The number of stratifications of the cumulative distribution is equal to the number of iterations performed. In the example above there were 5 iterations and thus 5 stratifications were made to the cumulative distribution. A sample is taken from each stratification. However, once a sample is taken from a stratification, this stratification is not sampled from again; its value is already represented in the sampled set (@RISK, 2002).

CHAPTER 3

GEOLOGY OF THE STUDY AREA

3.1 Regional Geological History

3.1.1 Introduction

A volumetric calculation of hydrocarbon resources is an estimation of the pore-volume of subsurface rock that contains oil or gas. The volume is derived from the thickness of the reservoir and the areal extent of the accumulation. Important geological considerations in establishing realistic estimates of pore-volume include the depositional environment of the reservoir, the history of its structural deformation, the trapping mechanism for hydrocarbon accumulation, and the position of the fluid interfaces. Therefore, it is essential to understand the geological setting and depositional environment of the study area.

3.1.2 Geological Setting

The Arabian Peninsula is set off from Africa by the Red Sea, from Iran by the Arabian Gulf and the Gulf of Oman, and is bounded on the south by the Arabian Sea and the Gulf of Aden. Figure 3.1 is a generalized geological map of the Arabian Peninsula that covers the study area. The Arabian shield, Arabian shelf, and the mobile belt are the three main geotectonic components that characterize the area. The Arabian shield is a vast complex of largely Precambrian igneous and metamorphic rocks that occupy about one-third of the Peninsula. To the north and northeast of the shield is the Arabian shelf which is characterized by a sequence of shallow water and continental sediments. The mobile belt is located north and east of the shelf that includes the Zagros and Oman Mountains (Alsharhan & Kendall, 1986; Saudi Aramco, 1977).

3.1.3 Stratigraphic History

The sedimentary section exposed above the Precambrian shield falls naturally into eight broad divisions (Saudi Aramco, 1977). From oldest to youngest, these are:

1- Early Paleozoic clastic rocks

2- Permian and Triassic clastic rocks

3- Lower and Middle Jurassic clastic and carbonate rocks

4- Upper Jurassic and early Lower Cretaceous carbonate rocks

5- Late Lower Cretaceous clastic rocks

6- Middle Cretaceous clastic rocks

7- Upper Cretaceous to Eocene carbonates rocks

8- Miocene and Pliocene clastic rocks.

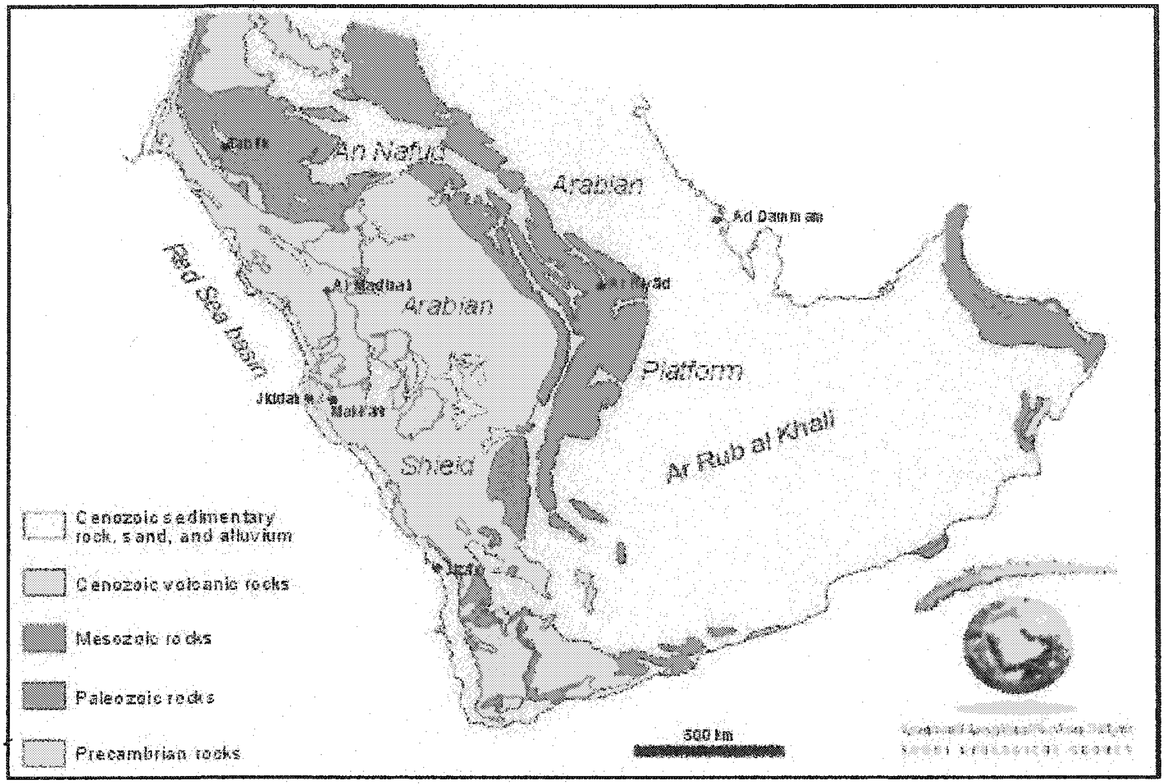


Figure 3.1: Generalized geological map of the Arabian Peninsula (From www.sgs.org.sa, 2002).

Following the deposition of the Paleozoic sediments, the Mesozoic and Cenozoic Eras were important to the Paleozoic petroleum system for two primary reasons. First, the deposition of a thick sedimentary sequence was responsible for the burial required to mature the potential Paleozoic source beds. Second, the tectonic events during these periods were responsible for the structural adjustments of the reservoirs/traps and the enhancement of the hydrocarbon migration routes (Husseini & McGillivary, 1992).

3.1.4 Mesozoic Deposition

Throughout the Mesozoic, the northeast passive margin of the Afro-Arabian Plate evolved as an extensive continental shelf, several thousands of kilometers in length and about two thousands kilometers wide (Murris, 1980; Beydoun, 1991). It was bounded on the northeast by the open neo-Tethys ocean and on the west and south by the basement outcrops of the Arabian Shield. During the Jurassic and most of the Cretaceous system, the Mesozoic deposition in the Arabian Gulf region was characterized by platform carbonates (Beydoun, 1991).

Differential subsidence within the shelf, combined with a rise in sea level, led to the formation of short-lived intra-shelf basins. Three basins formed in the Arabian Gulf region. A deep-water basin, the Gotnia Basin, existed in the northern Gulf region from the Middle Jurassic to Early Cretaceous (Murris, 1980; Ayres et al., 1982). The Southern Gulf basin, located in the eastern Qatar and western Abu Dhabi area, existed from late Callovian to early Kimmeridgian time (Alsharhan & Kendall, 1986). Ayres et al (1982) also recognized a third basin in which Ghawar and its related fields lie in the Saudi Arabia region. These three main Jurassic intrashelf basins (Figure 3.2) acted as the main source to hydrocarbons of the Jurassic-Early Cretaceous reservoirs (Alsharhan & Kendall, 1986).

Throughout the Callovian to the middle Kimmeridgian, the fluctuating sea level and differential subsidence resulted in the deposition and interfingering of source rocks and sub-regional seals. From late Callovian through middle Oxfordian high sea level, combined with differential subsidence of the basin, resulted in the deposition of a very thick source rock unit within the intraplatform basin (Figure 3.3), (Husseini, 1997).

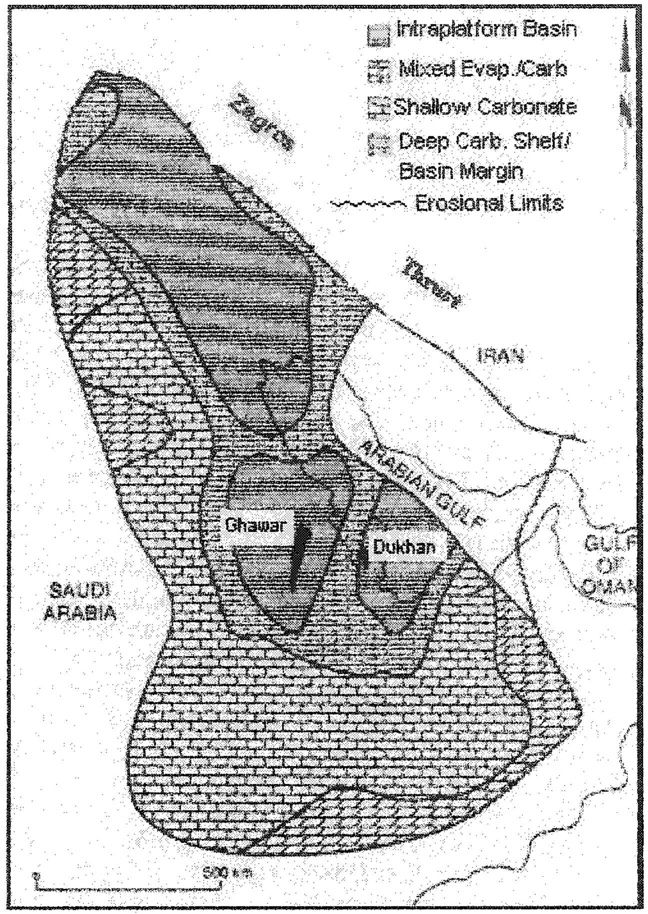


Figure 3.2: Three main Jurassic intrashelf basins of the Arabian Gulf area, which acted as the main source to hydrocarbons of the Jurassic-Early Cretaceous reservoirs (From Alsharhan, 1986).

The uniform sedimentary layering, typical of the Dhruma Formation, was changed in late Callovian to a clear separation of shallow water shelf facies to the north and deeper basinal facies in the interior of the Arabian Basin. Cyclical changes in sea level led to the development of a stacked sequence of shallow upward carbonate platform sequences on the Northern Shelf: Upper Fadhili, Hadriya and Hanifa reservoirs.

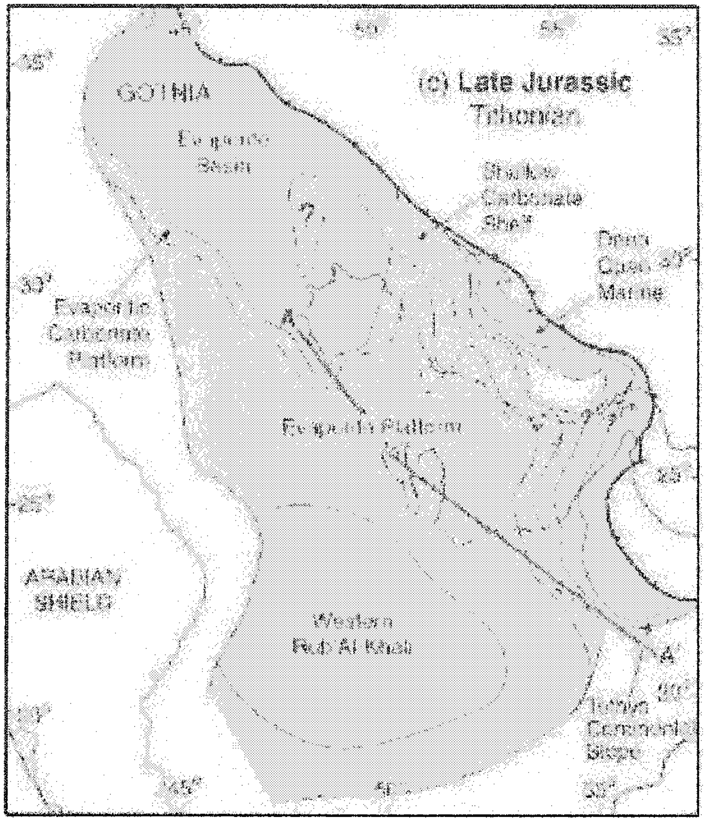


Figure 3.3: During Late Jurassic source rocks were deposited in broad intra-shelf basins (From Husseini, 1997).

Overall regressive conditions returned by the late Oxfordian, and shallow shelf facies of carbonates and evaporites gradually filled the basin. The Arab Formation contains four shallow upward cycles of grainstone-evaporites. The grainstones comprise the most important reservoirs in Saudi Arabia, which are the Arab-A, B, C, and D reservoirs. A thick sequence of evaporites, the Hith Formation, concluded the Jurassic and forms the principal regional seal to the Jurassic-sourced oil (Cole et al, 1996).

3.1.5 Conditions of Hydrocarbon Accumulation

There are certain factors to be satisfied for a good hydrocarbon accumulation: source rocks, good maturation conditions, reservoir rocks and traps. Source rocks are very important because without them there would be no hydrocarbon.

Saudi Arabia is one of the largest oil producing regions of the world where approximately 26% of the world's known oil reserves. About two-third of the oil reserves are found in Jurassic carbonate reservoirs. Cretaceous and Upper Paleozoic reservoirs of the Arabian Basin and the central part of Saudi Arabia contain the remaining part of hydrocarbons. The Jurassic Callovian to Oxfordian organic-rich carbonates are considered the source for hydrocarbon accumulations (Cole et al, 1994).

Source Rocks

A source rock is defined as a rock that generates and expelles hydrocarbons in sufficient quantity to form a commercial accumulation. The rock must meet minimum criteria for organic richness, kerogen type, and thermal maturation (Ayres et al, 1982).

The most important parameter for good hydrocarbon potential in any area is the availability of extensively deposited organic-rich source rocks. These rocks must be matured sufficiently to be capable of generating hydrocarbons and charging suitably placed carrier formations in order to permit commercially viable amounts of hydrocarbons to accumulate in integral traps under efficient seals. Most of the producing hydrocarbon reservoirs in the Arabian plate are Mesozoic in age, particularly, Middle Jurassic to mid-Cretaceous (Beydoun, 1991).

Geochemical studies have satisfactorily traced back the Saudi Arabian Mesozoic oils to Mesozoic source rocks. The Mesozoic source rocks of the Eastern Arabian region are of good quality but not sufficiently as thick as compared with those in other basins elsewhere in the world (Cole et al, 1994). The Jurassic (Callovian to Oxfordian) interval has been identified as having an organic-rich carbonate source rock. The corresponding oils are mainly from thinly laminated, thermally mature, organic-rich carbonate source rocks from Hanifa and Tuwaiq Mountain source rocks (Ayres et al, 1982).

Seals and Reservoirs

The best producer reservoirs are those where rocks with good porosity and permeability lie directly beneath efficient and extensive seals (Beydoun, 1988). For the Mesozoic reservoirs, seals are numerous and effective regionally. Evaporite seals are localized and can be intermixed with argillaceous seals. For the Upper Jurassic reservoirs, evaporites are the principal seals in the Eastern Arabia-Gulf region. These are mainly sabkha-type anhydrites. The Cretaceous reservoirs are essentially sealed by shales. The seal efficiency varies considerably in the more tectonically deformed parts of the Eastern Arabian Plate and it has permitted upward leakage into the younger Cretaceous reservoirs (Ayres et al, 1982).

In Saudi Arabia most oil accumulated in Jurassic reservoirs (Arab-A, B, C, D) sealed with the Hith Anhydrite, evaporite unit, averaging 500 ft (167 m) in thickness which forms an extensive seal that has prevented upward movement of oil generated in Jurassic source rocks. The Hanifa source rock forms a good seal to reservoirs of the Dhruma or Tuwaiq formation (Murris, 1980).

Traps

There are several definitions for traps. A trap is a geological feature which enables the migration of oil to accumulate and be preserved for a certain time interval, (Tissot & Welte, 1978). Another definition for trap is a place where oil and gas are barred from further movement, (Selley, 1985).

Structural traps are formed mainly as a result of tectonics occurring during or after deposition of the trap rocks. Structural trap style can vary from simple anticline to very complex structures with faults and folds depending on the stress regime that had been involved in their formation (Link, 1987). Most discovered oil fields have structural traps, (Selley, 1985).

Out of the structural traps, anticlinal structures are most common (Tissot & Welte, 1978). Eight out of the ten giant oil and gas fields in the world have anticlinal traps (Table 1), (Michel & Halbouty, 1986).

The main traps on the plains of the northeast Arabian margin are very large anticlines mostly with a north-south orientation. They include quite a number of 'super giant' and many 'giant' oil fields, with smaller more subtle subsidiary closures between them (Beydoun, 1991).

Field Name	Discovery Year	Country	Hydrocarbon Type	Trap Type	Geological Age
Ghawar	1948	Saudi Arabia	OIL	Anticline	Jurassic
Burgan	1938	Kuwait	OIL	Anticline	Cretaceous
Urengoy	1966	USSR	GAS	Anticline	Cretaceous
Safaniya	1951	Saudi Arabia	OIL	Anticline	Cretaceous
Bolivar Coastal	1917	Venezuela	OIL	Stratigraphic	Miocene
Yamburg	1969	USSR	GAS	Board Arch	Cretaceous
Bovanenkovo	1971	USSR	GAS	Anticline	Cretaceous
Cantarell Complex	1976	Mexico	OIL	Fltd. Anticline	Cretaceous
Zakum	1964	Abu Dhabi	OIL	Anticline	Jurassic
Hanifa	1957	Saudi Arabia	OIL	Anticline	Cretaceous

Table 1.1: Giant Oil and Gas Fields (Michel & Halbouty, 1986)

3.2 Arab-D Reservoir Geology

The Arab-D reservoir is the primary productive reservoir in the study area. The following is a brief discussion of the geologic framework of the Arab-D reservoir (Saudi Aramco, 1999).

3.2.1 Background of the Study Area

The study area is located onshore in the Eastern Province of Saudi Arabia. Arab-D formation is part of the upper Jurassic section in Saudi Arabia as shown in Figure 3.4. This Jurassic section is the largest hydrocarbon play in the history of world oil industry. About 17% of the world's oil and 67% of Saudi Arabia's oil are located in this section. The Jurassic section is divided into seven Formations, which are from oldest to youngest: Marrat, Dhruma, Tuwaiq Mountain, Hanifa, Jubaila, Arab and Hith Formations (Figure 3.4). Traps are mainly anticlinal (crest and flank traps) formed from draping of sediments over basement horst blocks. The primary regional seal is the massive (150 m-thick) evaporites of the Upper Jurassic Hith Formation overlying the Arab Formation (Saudi Aramco, 1999).

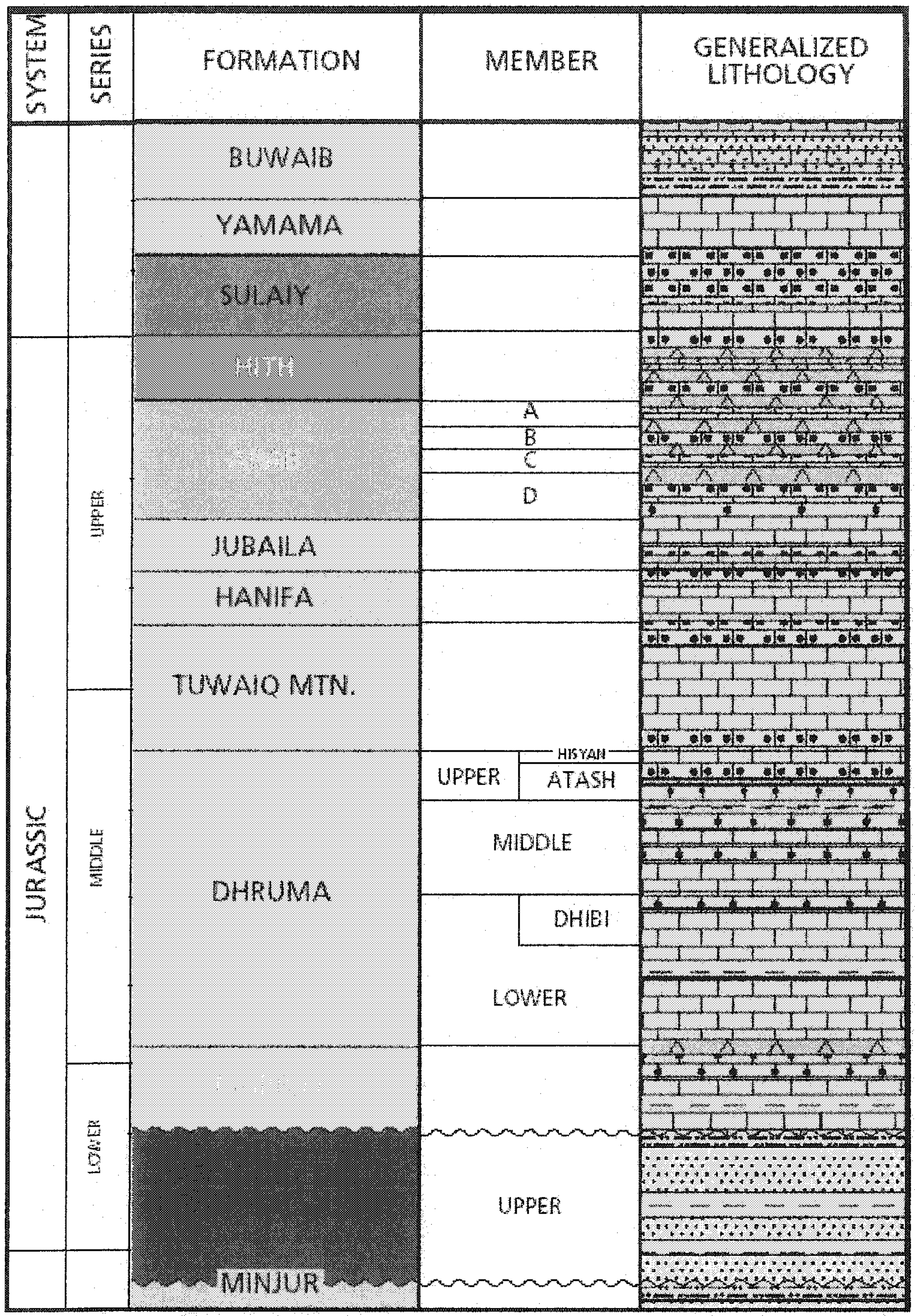


Figure 3.4: Generalized Eastern Saudi Arabian stratigraphy of the Jurassic (From Saudi Aramco, 1999).

3.2.2 Sediments of the Arab-D Reservoir

The Arab-D sediments consist of anhydrite, dolomite, and limestone. The anhydrite is only important in the non-reservoir part of the Arab-D member. Practically all fabrics present in the Arab-D anhydrites are modifications of nodular texture. With the exception of the laminated fabric, all petrographic attributes of the Arab-D anhydritic rocks have near perfect matching analogues in modern Sabkha complexes (Saudi Aramco, 1999). The grains of Arab-D sediments are skeletal and non-skeletal. Calcareous algae, foraminifera, and stromatoporoids are thin main skeletal grains. Non-skeletal grain type includes pelletoids, rounded aggregates, algal nodules, and coated grains. Calcitization and early recrystallization, formation of micritic envelopes, micritization, cementation, solution-compaction, and dolomitization are the main diagenetic processes affecting the Arab-D sediments in the study area (Saudi Aramco, 2001).

3.2.3 Lithofacies Types

Saudi Aramco geologists (Saudi Aramco, 1999) observed the following lithofacies types in the study area:

Mudstones and Wackestones

Mud sediments consisting largely of silt and clay size particles with several types of allochem fragments occur frequently throughout the study area. Environmental interpretation of uniform mudstones and wackestones implies that they may have formed in relatively low energy environment. They have been deposited in a shallow water sub-tidal environment. Their primary porosity and permeability are very low. Secondary leaching of micrite has created moderate porosity and permeability at some places of the study area.

Grainstones

Grainstones are the most important type of sediment found in the Arab-D reservoir. They range in size from very fine sand to pebble and from poor sorted to well sorted. The grains are packed to various degrees but the highest degree of packing is rare. Most grains are extremely micritized with primary interparticle porosity. Moldic interparticle pore types are also present with cement filling up some of the primary pore space. The grainstones have been probably deposited in a high-energy shoal environment. They have high porosities (up to 30%) and permeabilities (sometimes above 2000 mD), as shown in Figure 3.5 (Saudi Aramco, 1999).

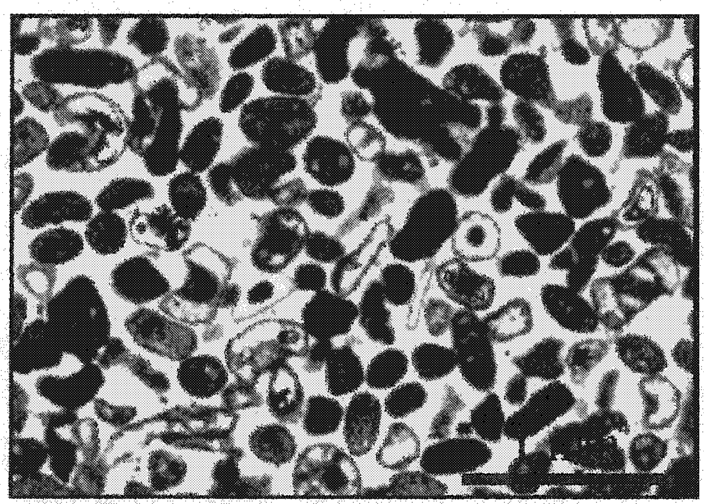


Figure 3.5: Thin section photomicrograph of grainstone with very good connectivity of pores. The blue color defines pore space (From Saudi Aramco, 1999).

Packstones

This lithofacies is found throughout the reservoir and shows a wide spectrum between wackestones and grainstones. While mud-low packstones and grainstones are more abundant in the upper portion of the reservoir, wackestones and packstones are more abundant in the lower part. Towards the top of the Arab-D reservoir packstones become less micritic and grade to grainstones indicating a shallowing upward sequence. A large variety of grain types are associated with packstones. Most abundant ones are pelletoids and skeletal particles. Stromatoporoids and cladocoropsis are also common and they increase the intra-particle porosity as shown in Figure 3.6. Packstones are deposited in a shallow subtidal environment. They have important pore types including primary interparticle and intraparticle voids and secondary grain moldic and micro-leached grain and matrix pores.

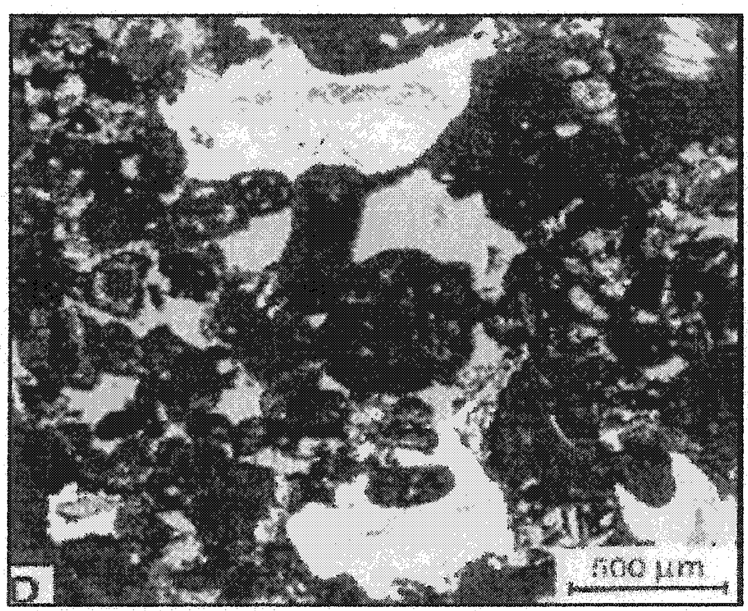


Figure 3.6: Thin section photomicrograph of sand size fragments of Cladocoropsis and other altered skeletal grains supporting a system of large interparticle pores; syntaxial cement occurs on echinoderm fragments. The blue color defines pore space (From Meyer et al, 2000).

Wackestones and Packstones

Pelletoidal lime packstones, and more commonly wackestones often associated with nerineid gastropod are common throughout the study area (Saudi Aramco, 1999). These units are intensely bioturbated with total loss of stratification and destruction of allochem. They may represent a shallow subtidal-intertidal environment of deposition. Porosities are generally in the range of 5-15%, and permeabilities between 1 to 10 mD. Micro-leached matrix and interparticle porosity in packstones are the main pore types.

Dolomite

As a minor component, dolomite occurs as scattered rhombs or as a replacement of one or more of the sediment components. The fabric rarely gives information on the original sediment type because of complete dolomitization. The texture of dolomites ranges from microcrystalline to medium crystalline (Figure 3.7). Remnants of an original grainstone texture were observed in thin sections of some dolomites. Also, a complete sequence of dolomitized grainstone ranging from undolomitized to completely dolomitized exists in the Arab-D, which indicates that the dolomitizing brines may have formed on the Sabkha by evaporation and then soaked through the grainstone forming brine lenses. Figure 3.8 shows dolomitic lime mud with low porosity (Saudi Aramco, 2001).

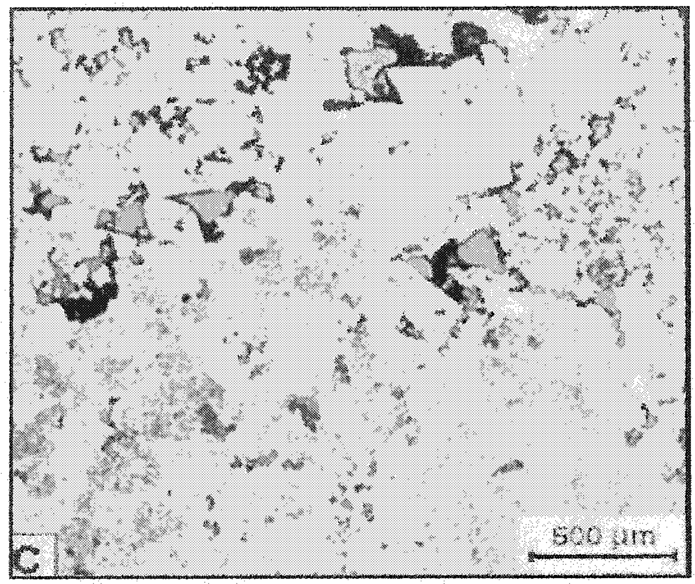


Figure 3.7: Thin section photomicrograph of a patchy development of intercrystalline pores characterizing the matrix porosity throughout the dolomite. The blue color defines pore space (From Meyer et al, 2000).

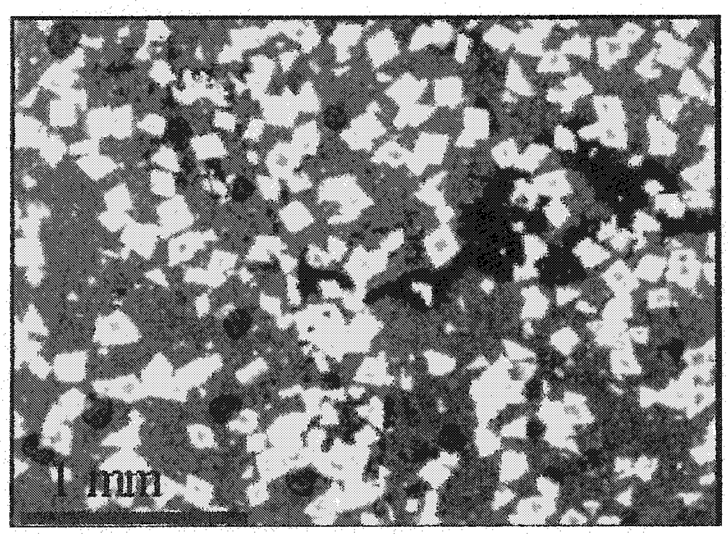


Figure 3.8: Thin section photomicrograph of dolomitic lime mud with low porosity. The blue color defines pore space, which is not clear in this case (From Saudi Aramco, 2001).

3.2.4 Arab-D Depositional Sequence

The Arab-D consists of two depositional units that accumulated during two major shallowing upward sequences and it is gradational with the underlying wackestones and packstones of the Jubaila Formation.

The lowermost cycle includes zone-2 and zone-3 and it consists of alternating beds of mudstones, coarser skeletal wackestones and/or packstones, and dolomites. Zone-3 contains more micritic carbonates, indicative of lower energy conditions. At the end of zone 2 deposition, a major sea-level rise submerged the shallow shelf, causing the start of a new cycle. A dolomite bed, 5-10 feet thick and persistent almost through the entire area, marks the boundary between zone-1 and zone-2.

The sequence of sediments suggests a depositional environment that was basically shallow marine throughout most of the period. Although zone-1 represents a major shallowing upward sequence, it includes at least three local transgressive units representing short-lived transgressions. During each of these transgressions the normal coarse shallow-water packstone and/or grainstone sequence was interrupted by the deposition of generally thin (3-5 feet) more micritic sediments of poor reservoir properties (Saudi Aramco, 2001).

CHAPTER 4

PORE-VOLUME ESTIMATION

4.1 Description of Reservoir Parameters

Computing volumes from reservoir thickness map can be done by manual contouring or by a computer. In this study, a deterministic 3D geocellular model has been prepared from integrating wireline-derived petrophysical and geological data. A porosity model is generated from porosity logs to calculate pore-volume. Statistical data analysis is the first step in reservoir modeling to investigate shape of data distribution. Statistical analysis is used to represent patterns of data by using simple arithmetic and graphical presentation. Probability is important in decision making because it provides a mechanism for measuring, expressing, and analyzing the uncertainties associated with events.

The study area is located in a productive basin in a carbonate reservoir of upper Jurassic. The structure is asymmetrical anticline, 15,500 meters long and 10,500 meters wide.

Saudi Aramco geologists have done detailed reservoir characterization using core analysis and logs. On basis of core data, three zones in Arab-D Reservoir are defined and correlated across the field (Saudi Aramco, 2000). Figure 4.1 shows a structure map at the top of the Arab-D Reservoir in the study area.

The size of the study area is 10,500 meters by 15,500 meters. This study followed Aramco's standard where areal cell dimensions are 250 x 250 meters. The model is 42 cells along the width, 62 cells along the length, and 123 cells along the depth. Total cells in the model are 320,292.

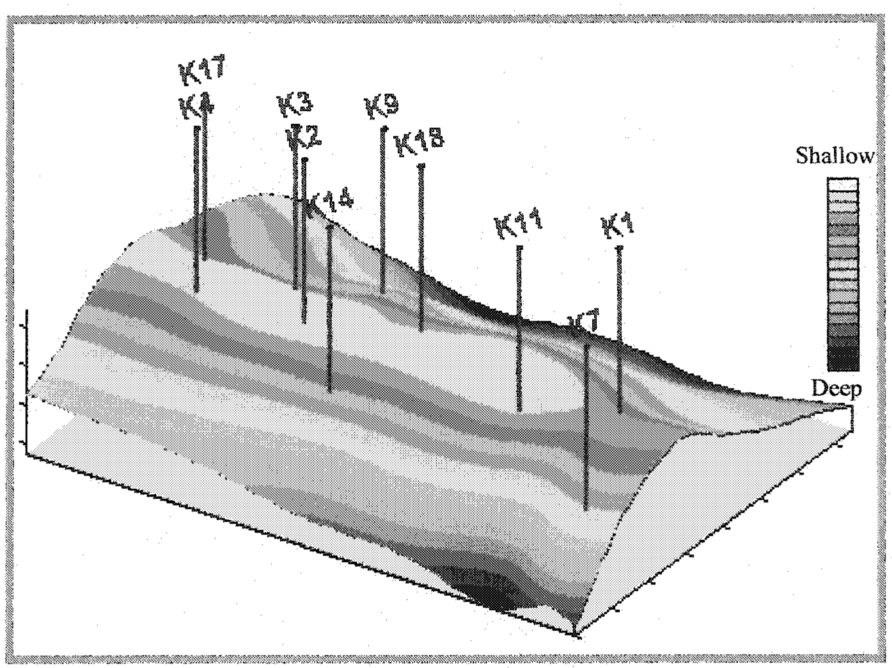


Figure 4.1: Structure map at the top of Arab-D Reservoir in the study area.

4.2 Review of Distribution Parameters

Statistics is a set of methods that are used to organize, analyze, present, and interpret data. In oil business and economics, statistics methods help in decision making in uncertain situations. The distribution of a random variable can be characterized by specific values, which tell us important information about the entire distribution. Two parameters are usually considered: 1) a measure of central tendency, 2) a measure of the variability, or the range within which the random variable is distributed, and 3) a measure of shape distribution.

4.2.1 Measures of Central Tendency

The distribution parameter which describe central tendency indicates average values of the random variable. Three measures of central tendency are common: the mean, median, and mode.

Mean:

It is the weighted average value of the random variable where weighting factors are the probabilities of occurrence. It is the expected value of a distribution, and is it is similar to the arithmetic average. All distributions (discrete and continuous) have means. The units of the mean are the same as the units of the random variable. From a statistical standpoint, the mean is the most important measure of the central tendency. It is likewise very important in decision making under uncertainty (Freedman et al, 1997).

Median:

It is the value of a random variable which divides the area under the probability distribution into two equal parts. It corresponds to the 50th percentile on a cumulative frequency distribution. For continuous random variables the probability of the random variable being less than or equal to the median is 0.50. If statistical data are listed in numerically increasing or decreasing order the median is the value half way down the list.

Mode:

The mode is the value of the random variable which is most likely to occur. It is the value of the random variable located under the highest, value of the distribution curve. The mode value is referenced frequently in the decision making process when we refer to the most likely values of random variables. Out of the three measures of central tendency, the mean is the most useful parameter (Freedman et al, 1997).

4.2.2 Measures of Variability

The mean of a distribution tells us important information about the average or expected value of the random variable, but it does not tell us about the spread or variability on either side of the mean. Single-value measures of variability are important in describing distributions. The most important measure of variability is the standard deviation.

Standard Deviation:

Each possible value of a random variable is located a given distance from the mean, as measured along the horizontal axis of the distribution. These distances are called deviations from the mean. The mean value of the squared deviations about the mean is called variance, and standard deviation is defined as the nonnegative square root of the variance. Most distributions have a standard deviation and its unit is identical to the units of the random variable.

The standard deviation defines the degree of spread or dispersion of the distribution around the mean value. The smaller the standard deviation, the narrower the spread or dispersion about the mean and vice versa. From a statistical point of view standard deviation is the most important measure of dispersion. Certain distributions such as the normal and lognormal are uniquely defined by specifying the mean and the standard deviation and are very useful in petroleum exploration analysis (DeVore, 1999).

4.2.3 Measures of Shape Distribution

Kurtosis is a measure of the shape of a distribution. Kurtosis characterizes the relative peakedness or flatness of a distribution compared with the normal distribution that has kurtosis of 3. Kurtosis greater than 3 indicates a relatively peaked distribution; kurtosis less than 3 indicates a relatively flat distribution. Skewness characterizes the degree of asymmetry of a distribution around its mean. Skewness measures the deviation of the distribution from symmetry. A skewness value grater than 1 or less than -1 indicates a highly skewed distribution. A value between .5 and -.5 indicates that the distribution is fairly symmetrical (Freedman et al, 1997).

4.2.3 Common Probability Distribution

The following probability distributions are frequently used in petroleum exploration analysis:

A- Normal Distribution

The normal distribution is one of the most common and widely used distribution in statistics and probability. It is a continuous probability function having a symmetrical bell shape. It is also called Gaussian distribution, after the German mathematician Karl Friedrich Gauss who developed the mathematical basis of the distribution. Some examples of random variables that can usually be represented by normal distribution are porosity and net pay as shown in Figure 4.2.

In normal distribution, mode, median, and mean are equal. The theoretical limits of a normal distribution are - ∞ and + ∞. The cumulative frequency graph of a normal distribution on linear graph paper has a stretched S shape. On a special graph paper (normal probability paper), the cumulative frequency distribution plots as a straight line (DeVore, 1999).

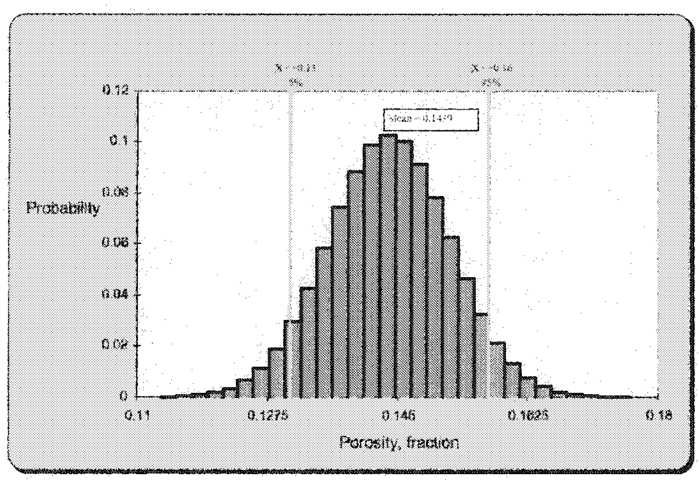


Figure 4.2: A sketch showing normal distribution.

B- Lognormal Distribution

Lognormal distribution is a continuous probability function similar to a normal distribution except that it is skewed to one side. The distribution can be skewed in either direction. Some examples of random variables that can be represented by lognormal distribution include core permeability, thickness of beds, and reserves as shown in Figure 4.3. If a random variable 'x' is lognormal distributed, the logarithms of the 'x' are normally distributed. The cumulative frequency graph of a lognormal distribution, when plotted on a special lognormal probability graph paper, is a straight line.

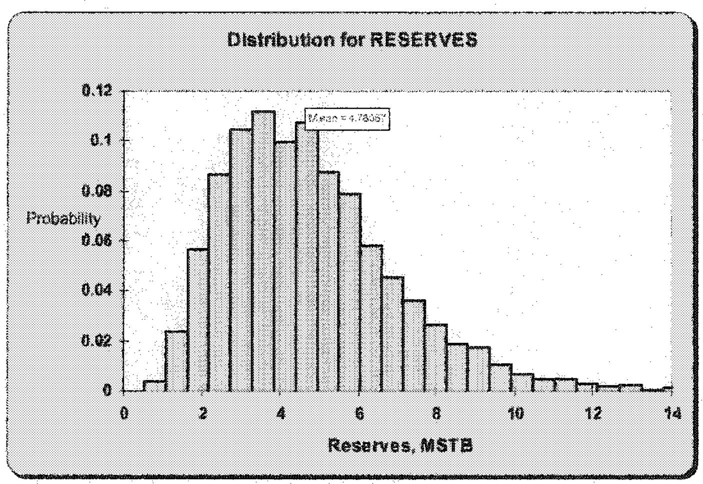


Figure 4.3: A sketch showing lognormal distribution.

C- Uniform Distribution

The uniform distribution is a continuous probability distribution describing a random variable in which any numerical value of the variable is equally likely to occur within an upper and lower limit. The uniform distribution is also called rectangular distribution as shown in Figure 4.4. The mean and the median of a uniform distribution are equal and they occur in the middle of the range between x_{min} and x_{max}. The cumulative frequency graph of a uniform distribution is a straight line on the arithmetic graph paper.

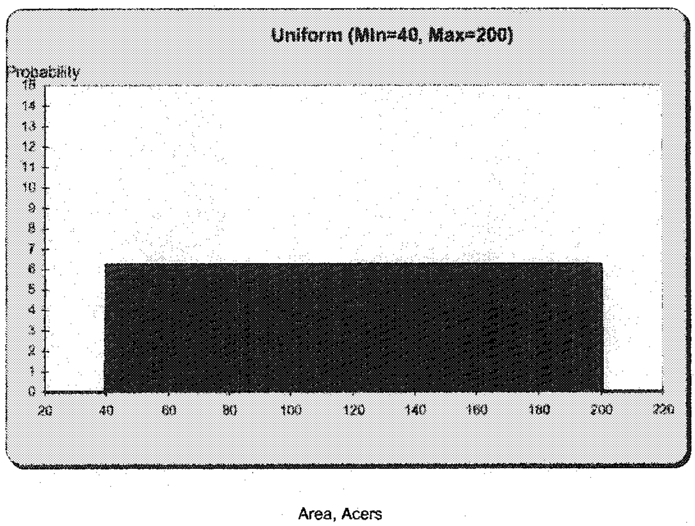


Figure 4.4: A sketch showing uniform distribution.

D- Triangular Distribution

The triangular distribution is a continuous probability distribution, which has a triangular shape. The triangle can be symmetrical or skewed in either direction. The mode can also be located at the minimum or maximum values of the random variable. The triangular distribution is completely defined by specifying the minimum and maximum values of the random variable as shown in Figure 4.5. It is commonly used to represent a distribution of the possible values of a random variable when the only information that is known or can be estimated is the minimum, most likely, and maximum values (DeVore, 1999).

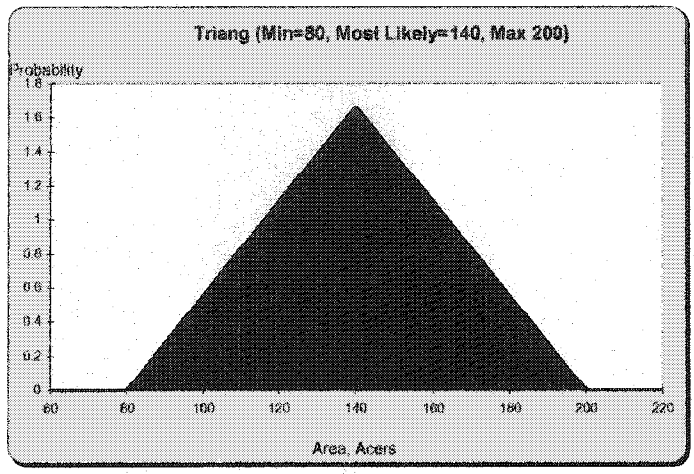


Figure 4.5: A sketch showing triangular distribution.

4.3 Deterministic Pore-volume Model

A deterministic estimate of oil volume is obtained by multiplying single values from geological and petrophysical parameters. In this study, the deterministic method integrates wireline-derived petrophysical and geological data using 3D geocellular reservoir modeling. In this methodology, various input parameters are single values and not distributions. In fact, the final deterministic oil pore-volume is just one outcome of a given interpretative process. This requires structural maps of the reservoir, determination of net pay thickness, and analysis of wireline logs to determine average porosity and fluid contacts.

4.3.1 Developing a Three-Dimensional Geocellular Reservoir Model

Stratamodel is 3-D modeling software that models the geology of the reservoir and allows better assessment of hydrocarbon volume (Cosentino, 2001). A 3D geocellular reservoir model requires petrophysical properties at wells, structural map for each geological unit, and petrophysical properties interpolation between wells to do volumetric calculations.

In this study, the following variety of data input techniques (Table 4.1) have been used:

- Structure grids, over which the reservoir is contained, were imported into Open-Works.
- Log data wells were imported through the Log ASCII Standard format. Then, the data surface and the well locations were created on the Dataset by typing in the surface coordinates and reference elevation.

• Well markers were imported through the raw files well information interface. An oil water-contact (OWC) grid was also loaded. The grid represents the distribution of the oil-water contact based on log picks from different wells.

• Reservoir Structure from Zmap + ASCII files.

• Top, bottom reservoir horizons, and intermediate horizons.

Table 4.1 Summary of methods used to load data.

Data Type	Source	Methods
Well Data	Geolog	OpenSpirit
Well Data	Open Works	ASCII
Well Location Data	OpenWorks	ASCII (SM 1)
Geol Markers	Data Base	ASCII
Structural Grids	Z-Map	ASCII (Zmap output)

4.3.1.1 Petrophysical Properties

Statistical analysis is essential to initiate a geological model. The analysis is important because it shows the location, spread and shape of data distribution. Distribution type is determined by generating histograms for the variables under study. The purpose of a histogram analysis is to control quality of input data and to gain a better understanding of the data.

The first step in developing a 3D reservoir computer model is to calculate petrophysical properties in each well using open-hole logs. Petrophysical properties from log analysis are first modeled by generating central tendency statistics and fitting the best probability functions to the data distributions. Properties input to the model include maps of porosity, and net pay by applying porosity cutoff, as a black box technique. These values are imported into Stratamodel and used as open-hole log attribute values. The sums and averages of the petrophysical properties in a given unit are used for calculation.

Porosity Statistics

Univariate statistical analysis has been conducted for porosity logs. The analysis is based on well logs that have a half-foot resolution. Porosity was determined by calibrating the sonic and neutron-density log to core-measured porosity (Figure 4.6). These analyses were conducted for all reservoir zones as a group (Figure 4.7) and for every individual reservoir zone (Figure 4.8 to Figure 4.10). Table 4.2 shows the porosity statistical parameters for all reservoir zones.

The porosity histogram for each zone suggests that porosity distribution is related to lithology. In the upper zones where good reservoir grainstones exist, porosity distribution tends to have normal distribution with high mean. In the lower zones where mudstone facies dominate, the porosity distribution tends to be positively skewed with a low mean porosity.

The upper zones, 1 and 2, are dominated by greenstone facies. This explains the high porosity values in these zones. The lower zone-3 is dominated by mudstone facies. This explains the low porosity of this zone and confirms that porosity distribution is directly related to facies.

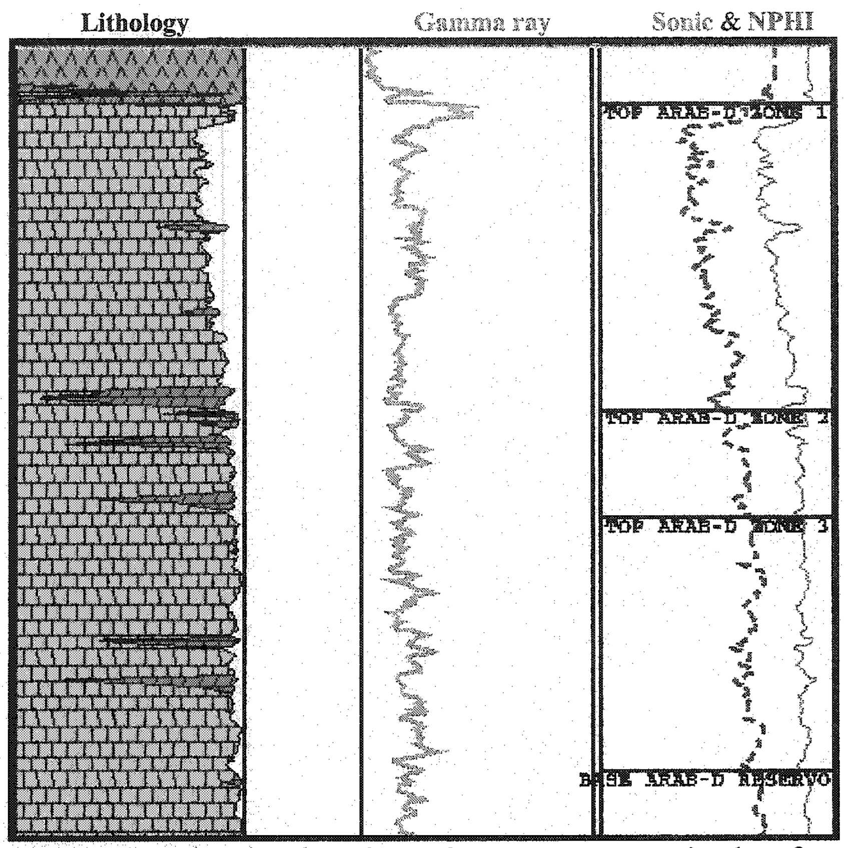


Figure 4.6: Type log showing layering schemes on a porosity log for the well across the Arab-D reservoir.

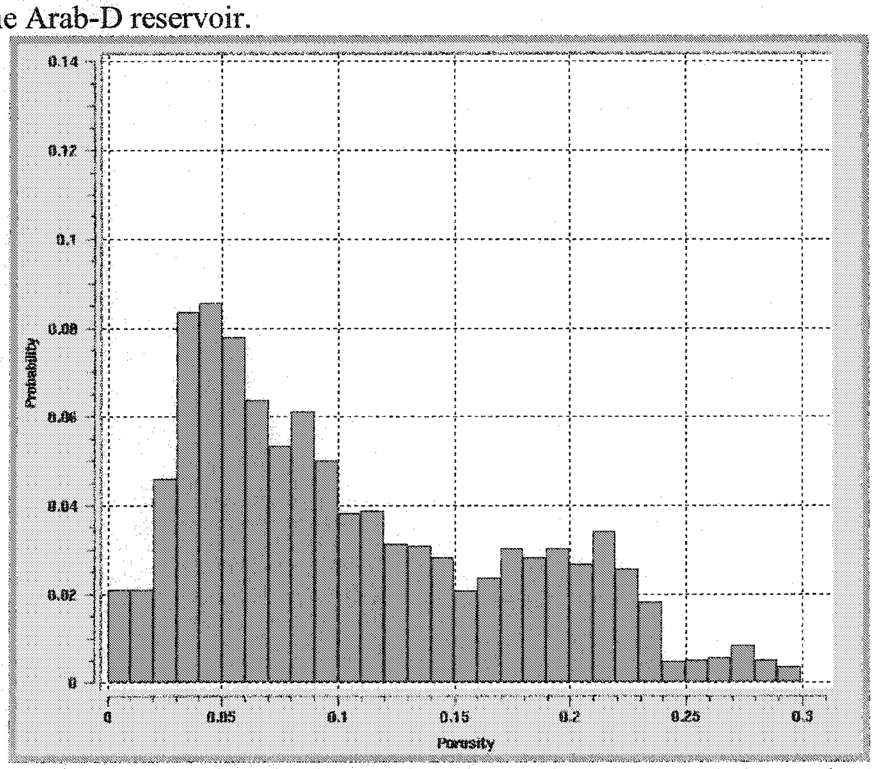


Figure 4.7: Porosity distribution within the Arab-D Reservoir in Study Area.

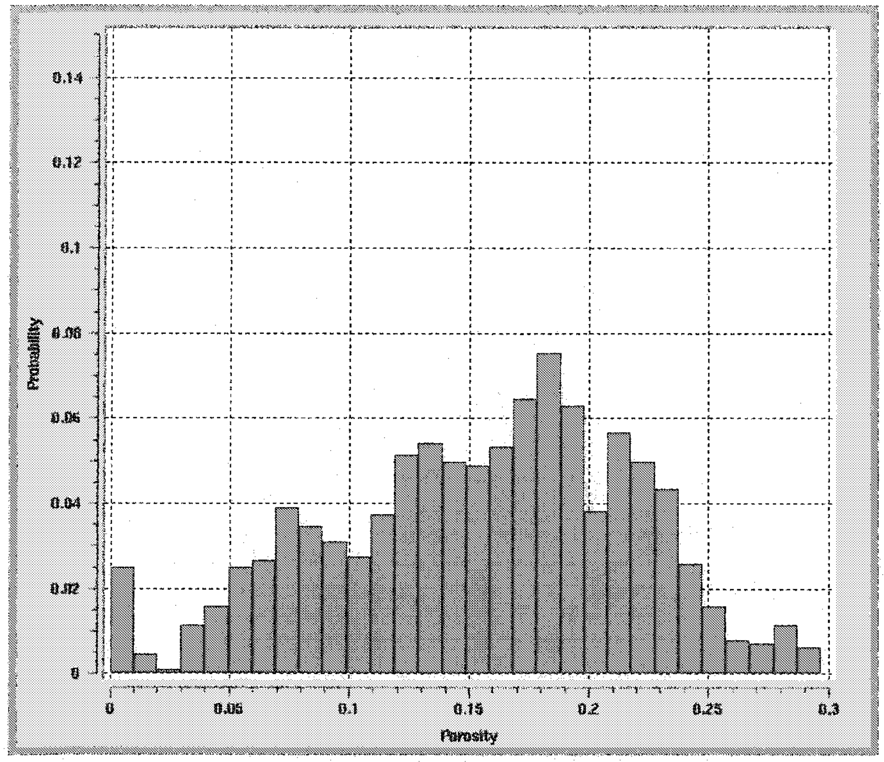


Figure 4.8: Porosity distribution in the zone-1 of Arab-D Reservoir.

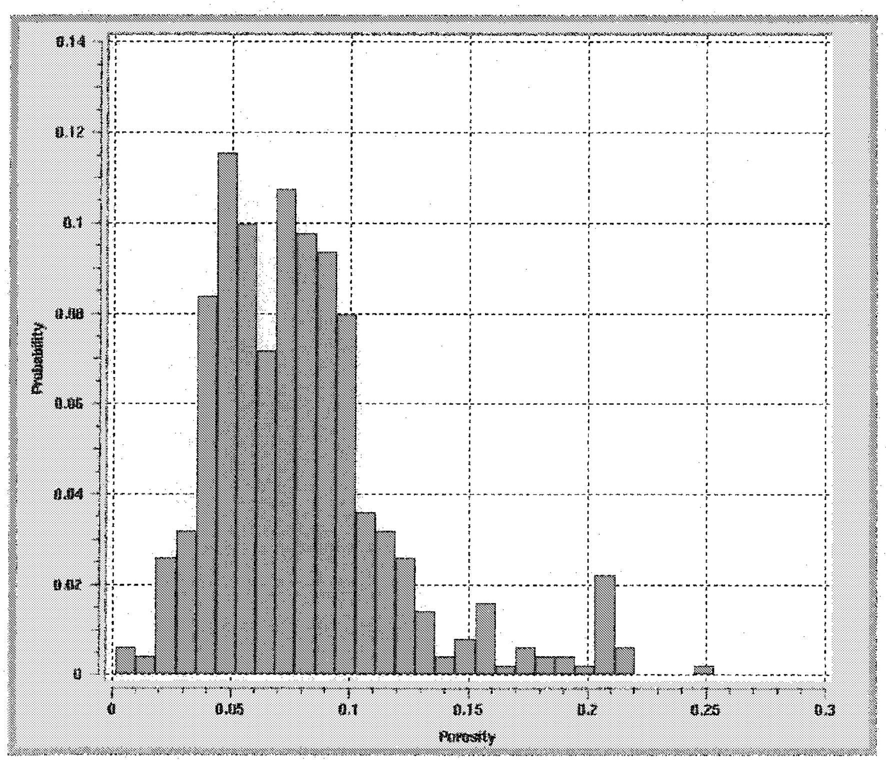


Figure 4.9: Porosity distribution in reservoir zone-2 of Arab-D Reservoir.

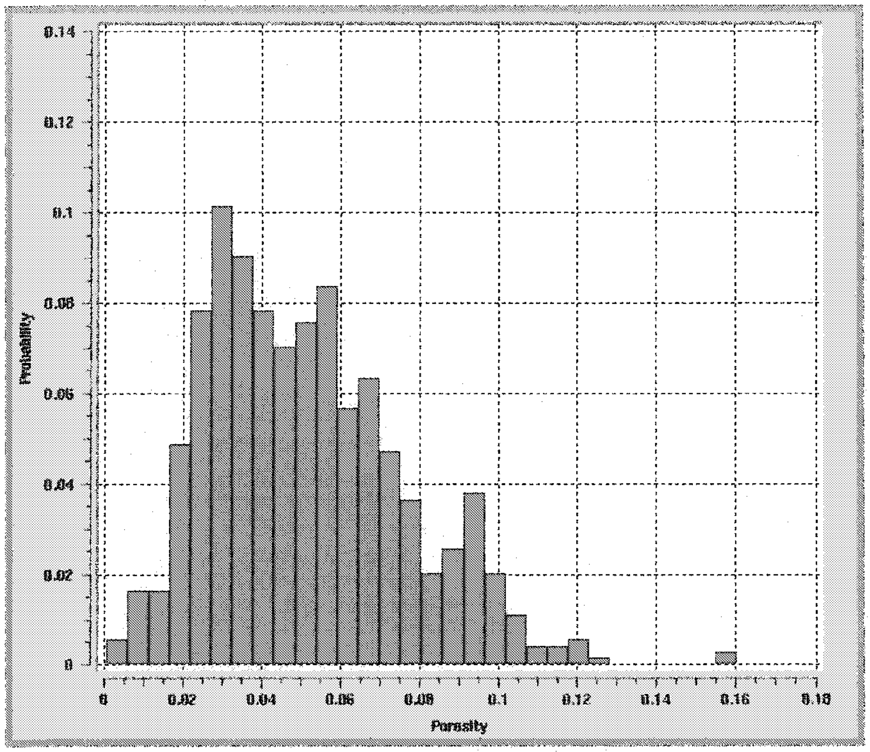


Figure 4.10: Porosity distribution in reservoir zone-3 of Arab-D Reservoir.

Zone Number	mean	median	minimum	maximum	standard deviation	coefficient variance
1	0.15	0.16	0.00	0.30	0.06	0.41
2	0.08	0.07	0.00	0.25	0.04	0.50
3	0.05	0.05	0.00	0.16	0.02	0.49
Arab-D	0.11	0.09	0.00	0.30	0.07	0.65

Table 4.2: Porosity statistical parameters for Arab-D Reservoir zones.

Net Pay Thickness

Net pay was determined from the porosity cutoff (5%) as a result from the log analysis using Geolog software. To deal with the reservoir heterogeneity and to optimize the number of cells thickness, the reservoir was divided into three zones. In the upper part of the reservoir, good quality rocks exist while poor quality in the lower section of the reservoir. Table 4.3 shows the thickness variations in each zone. The rock volume is obtained by integrating contour maps that describe net pay thickness between the crest of the accumulation and the hydrocarbon-water contact.

Table 4.3: Reservoir zones thickness.

Zone Number	Thickness (feet)			Standard Deviation
	Maximum	Minimum	Average	
1	104	88	95	4.67
2	54	31	42	6.72
3	97	65	82	8.09

4.3.1.2 Structural Gridding for Geological Units

The second step in building a 3D geocellular model is to create structural surface grids for each unit. Gross rock volume is calculated by integrating volume under top-reservoir depth structure map to Oil-Water Contact. Uncertainty in gross rock volume arises due to an uncertainty in either depth structure map or Oil–Water Contact. Depth structure map derived from seismic data is better with increasing number of control points (wells). Depth structure map at top-reservoir was converted to depth structure at individual zone tops by adding successive isopach maps.

The top Arab (seismic) time horizon was first converted into depth to provide structural closure above the expected Oil-Water Contact (Saudi Aramco, 2000). Available tops for each of the three reservoir units were then converted into depth. Each layer corresponds to a stratigraphic grid into which the available well-log data were resampled. Resampling is performed by intersecting each well trajectory with the layer to determine the corresponding well-populated grid-blocks, then averaging the measured log attributes within each intersected grid-block.

The seismic surface was used to represent depositional surface so that genetic unit isopachs could be added to generate each of the additional unit surfaces. The depth map at the top Arab-D depositional surface was based on 2D seismic data and well control points. The Arab-D reservoir was divided into zones and isopach maps were made for each zone. The isopach map of first zone was added to top Arab-D depth structure to generate depth structure at the top of second zone and so on. The maps were transformed using computer-generated grid files.

Next, the depositional top of the Arab-D was created by developing a surface on the top of zone-1 marker and isopaching down. Finally, the Arab-D of zone-2, zone-3, and base of the reservoir tops (Figure 4.11 to Figure 4.14) were created by applying conformable gridding of the wireline tops and seismic tops and adding isopachs.

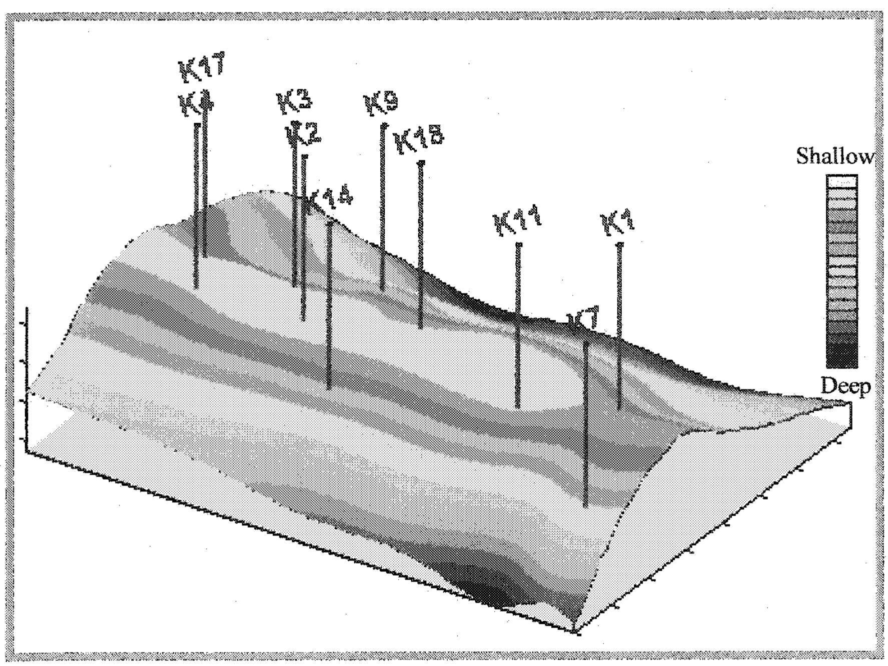


Figure 4.11: Structure map at the top zone-1 of Arab-D Reservoir.

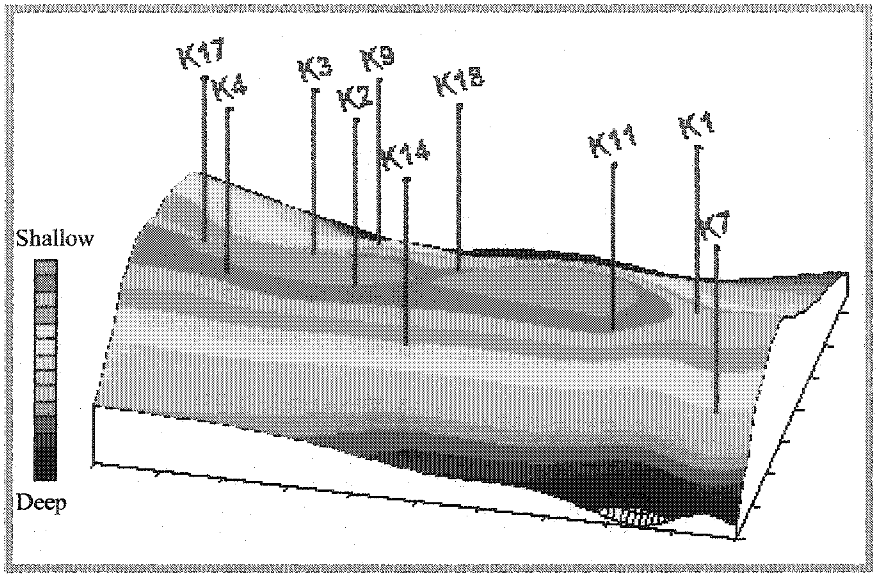


Figure 4.12: Structure map at the top zone-2 of Arab-D Reservoir.

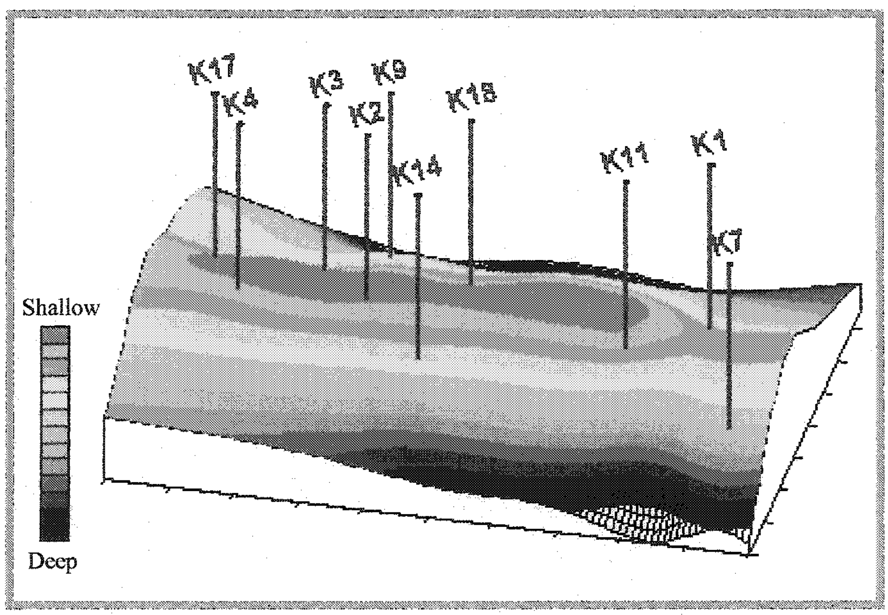


Figure 4.13: Structure map at the top zone-3 of Arab-D Reservoir.

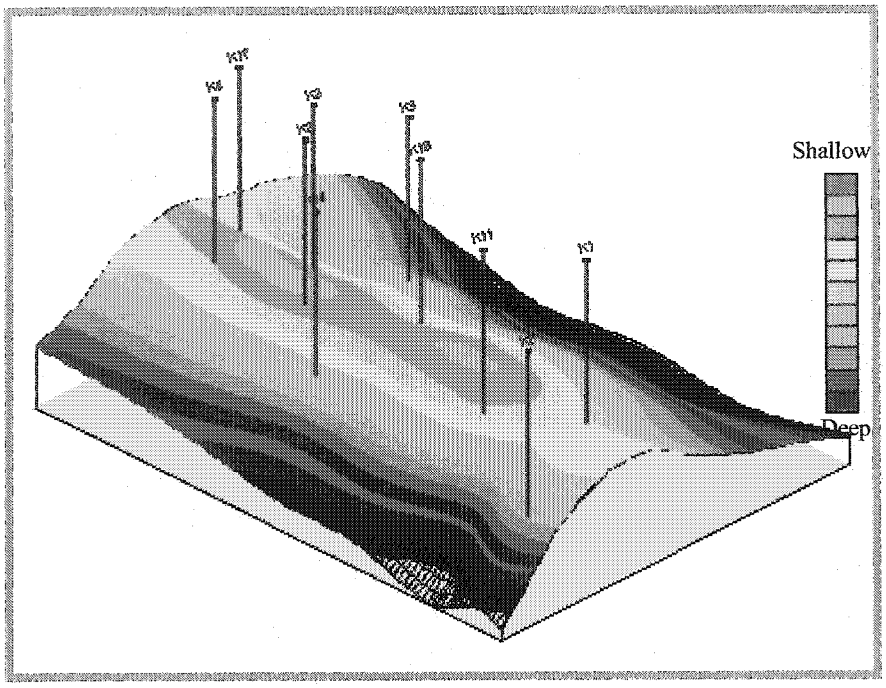


Figure 4.14: Structure map at the base of Arab-D Reservoir.

4.3.1.3 Interpolating Petrophysical Properties between Wells

Interpolating petrophysical properties between wells is the third step after preparing wireline petrophysical properties and developing subsurface grids.

The petrophysical parameters interpolation scheme applied to Arab-D reservoir was the inverse distance weighted interpolation which is one of the most commonly used techniques for interpolation of scatter points and used in this study for simplicity only. The basic principle of inverse distance is that data points are weighted by the inverse of their distance to the estimation point. Inverse distance weighted method is based on the assumption that the interpolating surface should be influenced most by the nearby points and less by the more distant points (DeVore, 1999). The interpolated Arab-D properties include porosity (Figure 4.15) and net thickness of the 5-percent cutoff, and oil-water contact grid surface.

4.3.2 Deterministic Pore-volume - Volumetric Calculation

Geocellular operations are the final step in developing a 3D reservoir model. Both attribute model equations and hydrocarbon volumetrics are accomplished in this step. Applying attribute model equations allows additional properties to be assigned to each cell in the model. The resulting reservoir map represents hydrocarbon porosity- thickness, which is integrated to calculate total pore-volume. Hydrocarbon volumetrics are determined by applying pay cutoffs, and input reservoir boundary map. The calculations were carried out for each zone separately and then summed up to obtain the total oil volume.

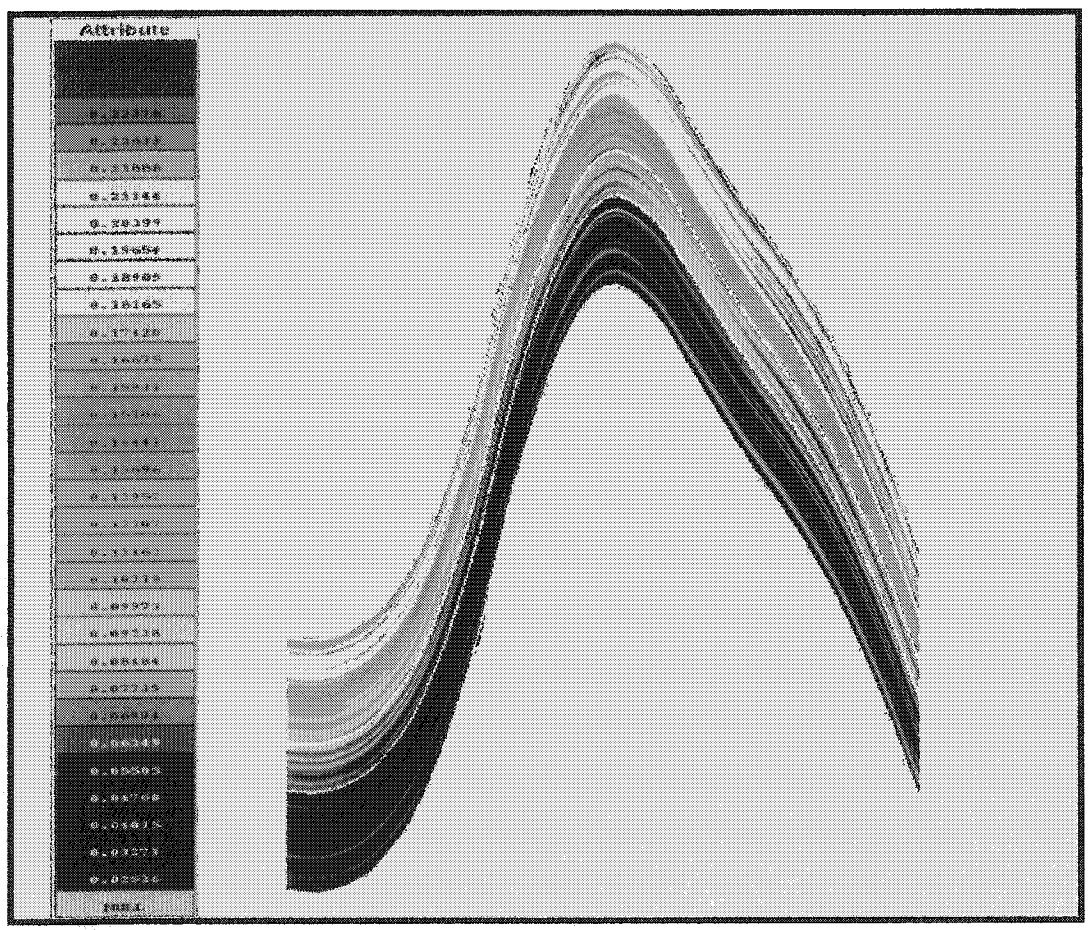


Figure 4.15: Cross section of porosity distribution for Arab-D reservoir (Attribute = Porosity).

4.4 Probabilistic / Stochastic Pore-volume Model

Probabilistic pore-volume is generated by integrating geologic parameters determined from a 3D deterministic computer model with statistical variation determined from probability functions of petrophysical attributes.

In this study, two Monte Carlo Simulation cases with 10,000 trials were run using @RISK software. @RISK is a software system for the analysis of business and technical situations impacted by risk. The techniques of Risk Analysis have long been recognized as powerful tools to help decision-makers successfully manage situations subject to uncertainty. @RISK is a system which brings these techniques to the industry standard spreadsheet package, Microsoft Excel. With @RISK and Excel, any risky situation can be modeled, from business to science and engineering (@RISK, 2002).

Two strategies were used in pore-volume evaluation. In one case, the reservoir was subdivided into three zones and their average properties were determined. Their pore-volume distributions for each zone were simulated individually and then aggregated also by using simulation. In second case no zonation was done and average properties were determined. The pore-volume distribution was simulated for the whole reservoir. In both simulations cases, three distribution functions are used as inputs: Net pay, Porosity, and Area.

Parameters in a model can be either "independent" or "dependent" and both cases were assumed in this study. An independent parameter is totally unaffected by any other parameter within the model. A dependent parameter is determined by one or more other variables in the model. It is extremely important to correctly recognize correlations between parameters. The Corrmat function in @RISK is used to identify correlated parameters.

4.4.1 Designing the Monte Carlo Simulation

Monte Carlo simulation begins with a statistical model. Two assumptions support this technique. First, there should be a mathematical model to calculate reservoir pore-volume. Second, the probability distributions of the reservoir parameters must be known.

The first step in Monte Carlo analysis is to define the average parameters by developing the deterministic model. The second step is to identify the uncertainty in the average parameters by specifying their probability distributions. The third step is the simulation. The model is run repeatedly to sample the range and probabilities of all possible outcomes of the model. During each run, an average value for each parameter is selected randomly from its specified probability distribution using a random number generator. As the Monte Carlo simulation is running, the model calculates and collects the results for analysis. The output sample is then presented as the overall probability distribution for the simulation using graphs such as histograms and cumulative distribution functions (CDF's) as well as descriptive statistics. Finally a probabilistic range of pore-volume is calculated using the Monte Carlo simulation. The following standard volumetric equation is used for calculating the pore-volume:

$$V_p = 7758\, A\, h\, \phi$$

where, V_p = pore-volume (acre-feet) converted to standard oil field units of acre-feet by multiplying with the constant 7758. A is the drainage area (acres) of the well multiplied by h (feet) which is the pay thickness at the wellbore, ϕ is the porosity (PSCIM, 1994).

4.4.2 Selecting Input Distributions

Each parameter in the calculations is represented by a probability distribution from a 3D deterministic model (frequency distribution). It is essential to obtain representative results. One may first search for the type of distribution which is most appropriate for a particular variable. Then, the probability functions are fitted to data distributions to quantify uncertainty.

A Monte Carlo simulation is commonly run with special software. The key step is to choose a value for each input parameter according to a specified distribution. The commonly used distributions are normal, triangular, lognormal, and uniform. Based on field data, the distribution may have a shape different from a theoretical distribution. These theoretical distributions and the grouped field data are represented as histograms, probability density functions (PDF), or cumulative distribution functions (CDF).

The sampling process requires only a CDF for the relevant parameter. The CDF are constructed for the field data, by grouping them into classes and then calculating the cumulative relative frequency. The minimum data required for probabilistic pore-volume calculations involve the following parameters: porosity, net pay thickness, and area.

The reservoir net pay varies continuously over the reservoir area and could be considered as a 3D volume in space. It is not representative to generate a net pay distribution using well values alone (wells measure net pay as a point), which vary over a range from 30 feet to 120 feet. Net pay and porosity data should be mapped over the reservoir area and then area-weighted averages should be calculated and used to generate input distribution for simulation. Therefore, average parameters estimated from the 3D geocellular model (deterministic) are used to generate input distributions (Figures 4.16 to

4.19). The map grids are converted to data, statistically analyzed, (Table-4.4) after applying 5-perecent cutoff and used to generate input parameter distributions (net pay and porosity) for Monte Carlo Simulation.

Twenty-five different parameter distributions were fit to the data using @Risk software and the best-fit distribution was then selected using Chi-square goodness-of-fit. By examining the range of results within the wells, an estimate can be made for the possible range of the average field values. It has been found that the normal function is the best to describe the frequency distribution of porosity values (Figure 4.20). The Chi-square, Anderson-Darling, and Kolmogorov-Smirnov statistical tests strongly suggest that the normal function is the best to represent the data distributions. The normal distribution also fits closely both area and net pay parameters (Figures 4.21 to 4.23). Table 4.5 is a summary of all statistical inputs used in this study for correlated versus non-correlated variables.

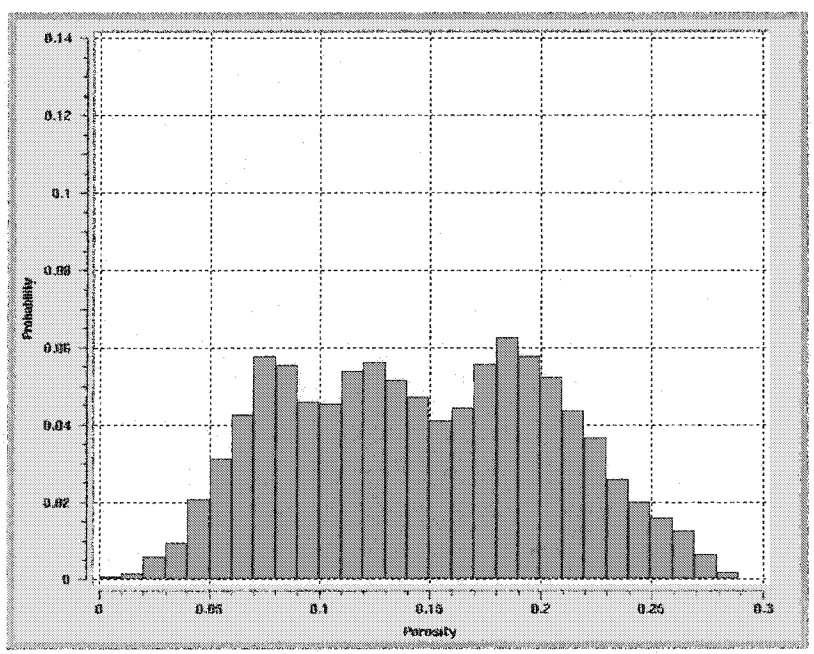


Figure 4.16: Porosity distribution from raw data within the Arab-D Reservoir in the Study Area.

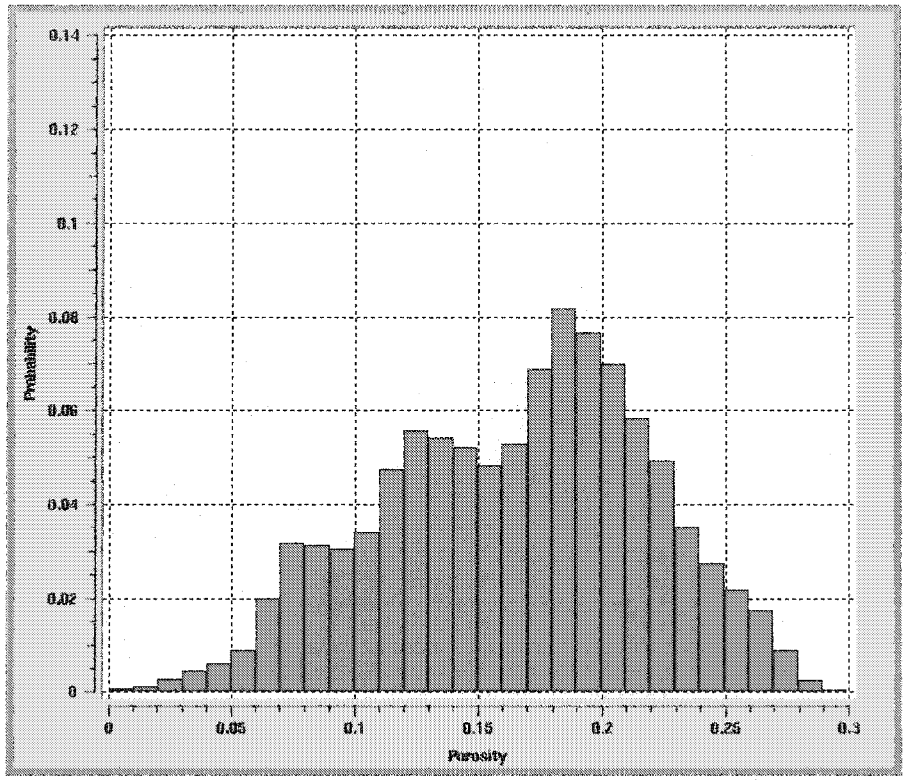


Figure 4.17: Porosity distribution from raw data in reservoir zone-1 of Arab-D Reservoir.

Zone Number	mean	median	minimum	maximum	standard deviation	coefficient variance
1	0.17	0.17	0.05	0.30	0.05	0.31
2	0.09	0.08	0.05	0.22	0.03	0.34
3	0.07	0.07	0.05	0.19	0.02	0.29

Table 4.4: Main porosity statistical parameters for Arab-D Reservoir by applying 5% porosity cutoff.

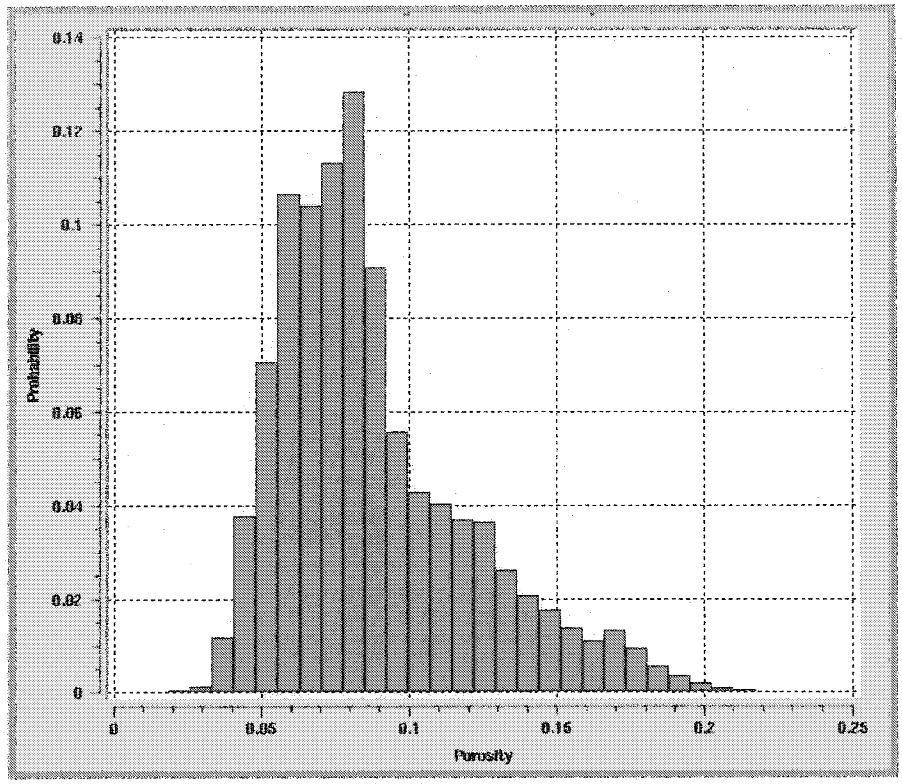


Figure 4.18: Porosity distribution from raw data in reservoir zone-2 of Arab-D Reservoir.

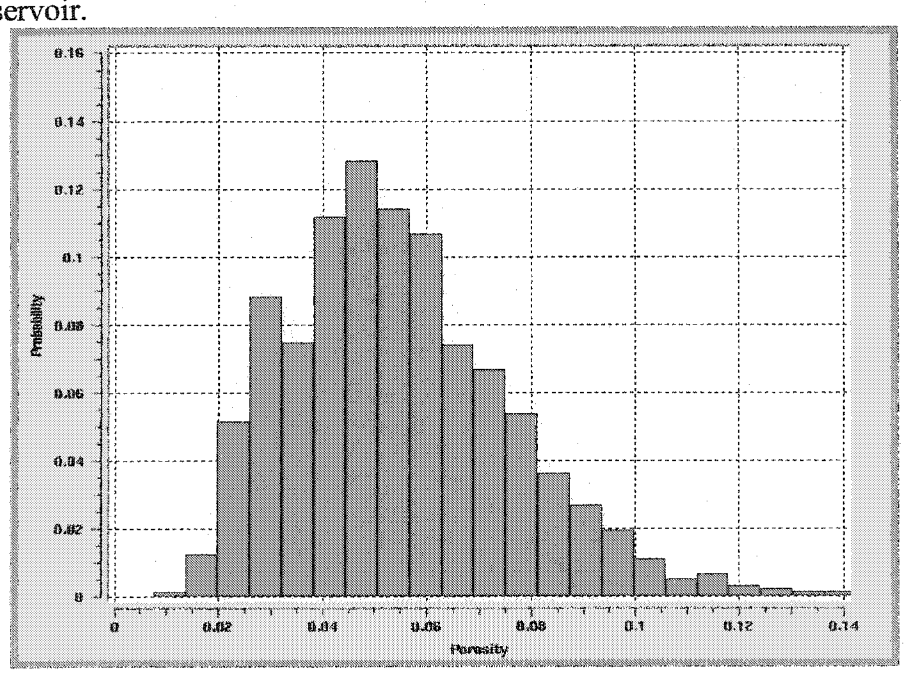


Figure 4.19: Porosity distribution from raw data in reservoir zone-3 of Arab-D Reservoir.

Table 4.5: Statistical inputs for simulation by Applying 5% porosity cutoff.

Input Name	Worksheet	Input Cell	Minimum	Maximum	Mean	Std Dev
Area	zone1	C29	57036.3	57165.0	57100.0	17.0
Area Correlated	zone1	G29	57034.5	57165.3	57100.0	17.0
Net Pay	zone1	C30	74.0	105.5	88.8	3.7
Net Pay Correlated	zone1	G30	72.7	105.8	88.8	3.7
Porosity	zone1	C31	0.10	0.17	0.14	0.01
Porosity Correlated	zone1	G31	0.10	0.17	0.14	0.01
Area	zone2	C29	25895.5	26030.8	25962.8	17.0
Area Correlated	zone2	G29	25892.3	26027.8	25962.8	17.0
Net Pay	zone2	C30	26.7	51.1	38.3	3.1
Net Pay Correlated	zone2	G30	25.7	50.5	38.3	3.1
Porosity	zone2	C31	0.06	0.10	0.08	0.01
Porosity Correlated	zone2	G31	0.06	0.10	0.08	0.01
Area	zone3	C29	14033.6	14161.4	14098.0	17.0
Area Correlated	zone3	G29	14018.2	14157.3	14090.0	17.0
Net Pay	zone3	C30	2.0	33.4	17.7	4.2
Net Pay Correlated	zone3	G30	2.0	36.3	17.7	4.2
Porosity	zone3	C31	0.05	0.08	0.07	0.00
Porosity Correlated	zone3	G31	0.06	0.08	0.07	0.00
Area	Total	C29	37032.4	37163.8	37100.0	17.0
Area Correlated	Total	H29	37027.3	37167.0	37100.0	17.0
Net Pay	Total	C30	89.9	161.9	125.3	9.2
Net Pay Correlated	Total	H30	90.4	165.8	125.3	9.2
Porosity	Total	C31	0.11	0.17	0.14	0.00
Porosity Correlated	Total	H31	0.11	0.18	0.14	0.00

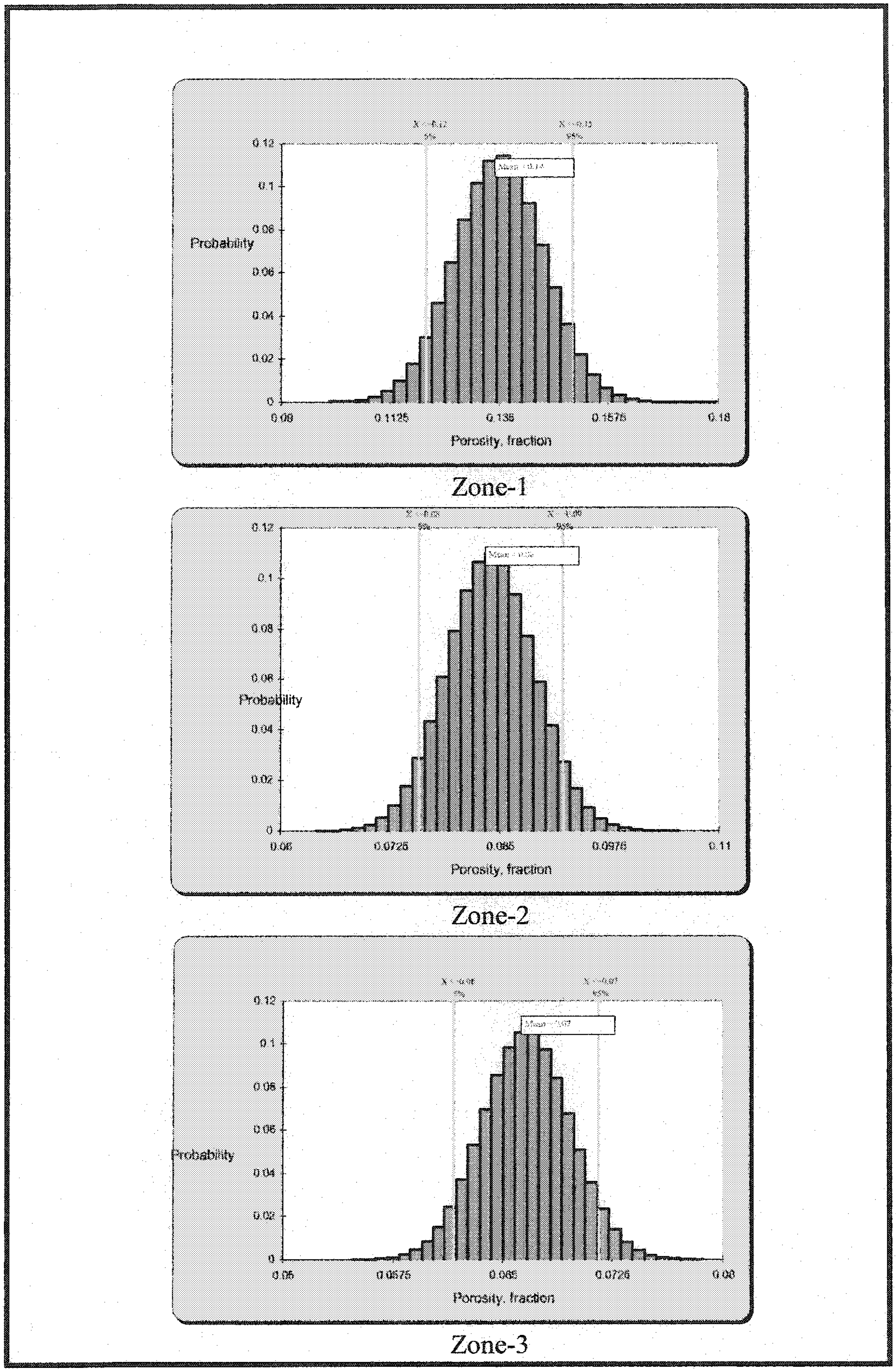


Figure 4.20: Input distribution of porosity by applying 5% cutoff for the three zones of Arab-D Reservoir.

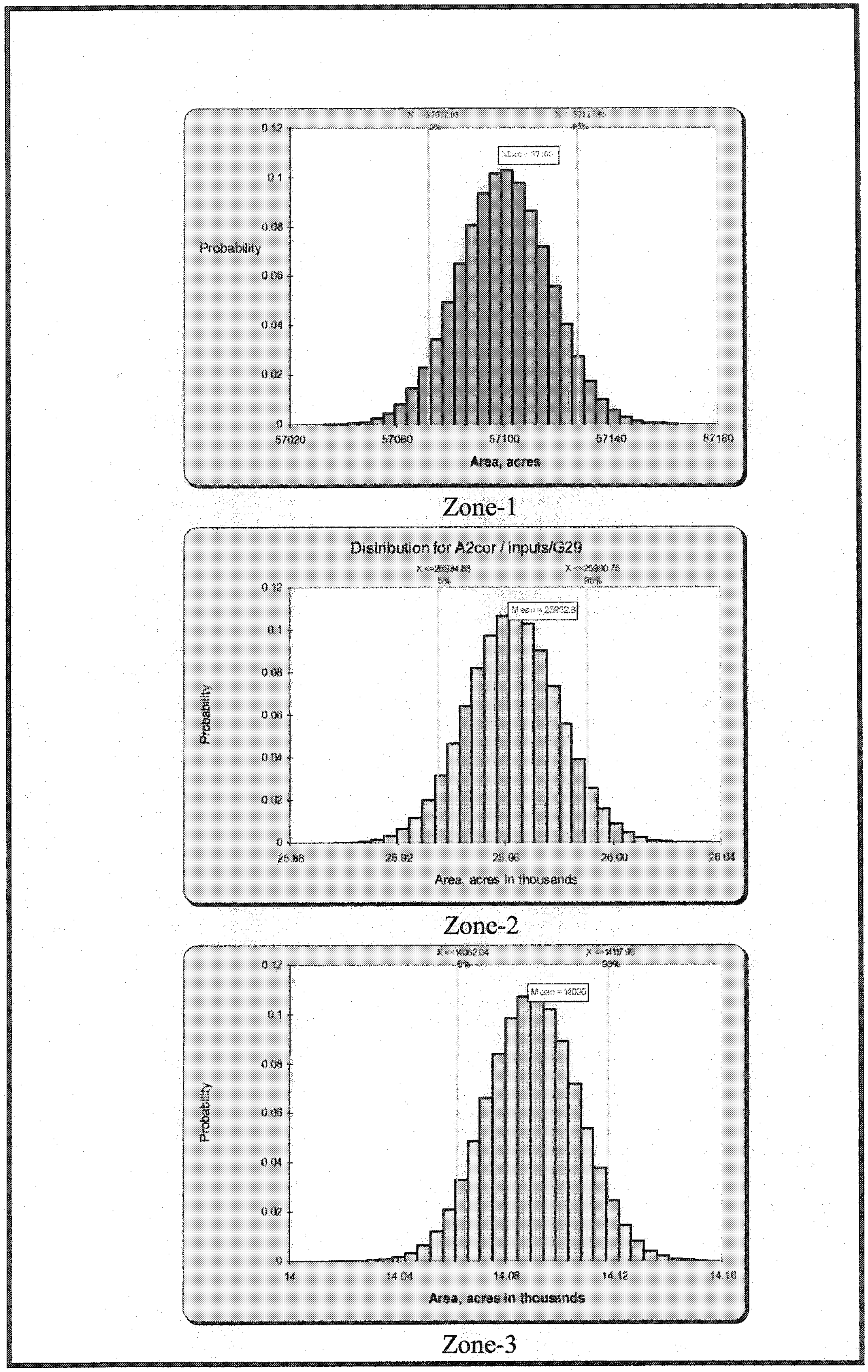
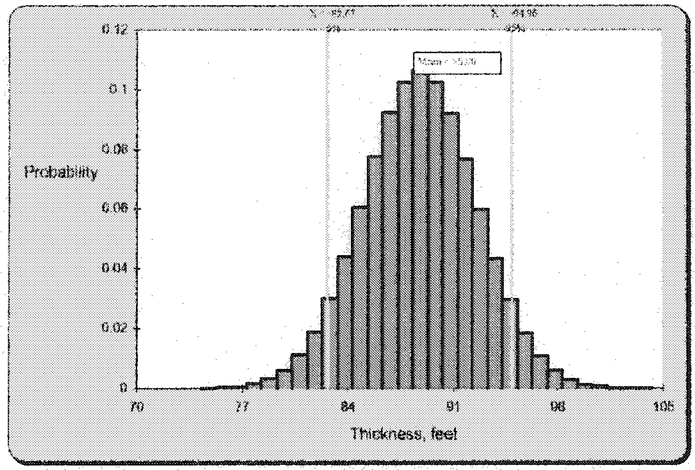
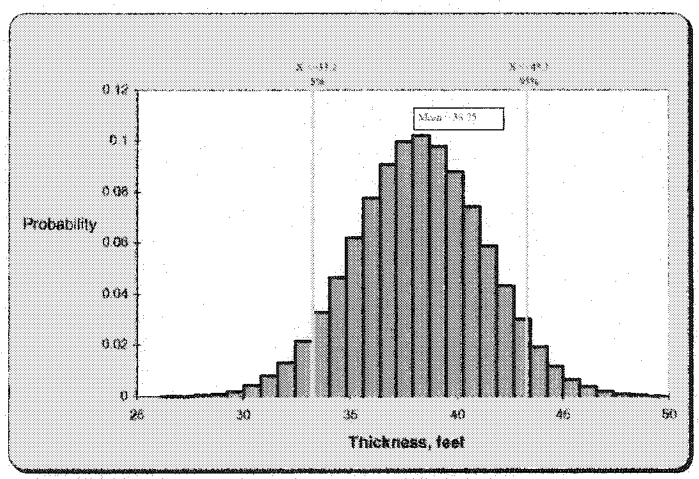


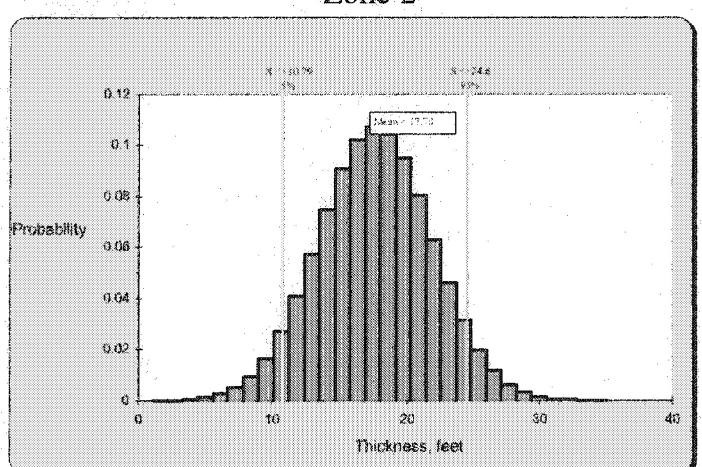
Figure 4.21: Input distribution of area for the three zones of Arab-D Reservoir.



Zone-1



Zone-2



Zone-3

Figure 4.22: Input distribution of thickness for the three zones of Arab-D Reservoir.

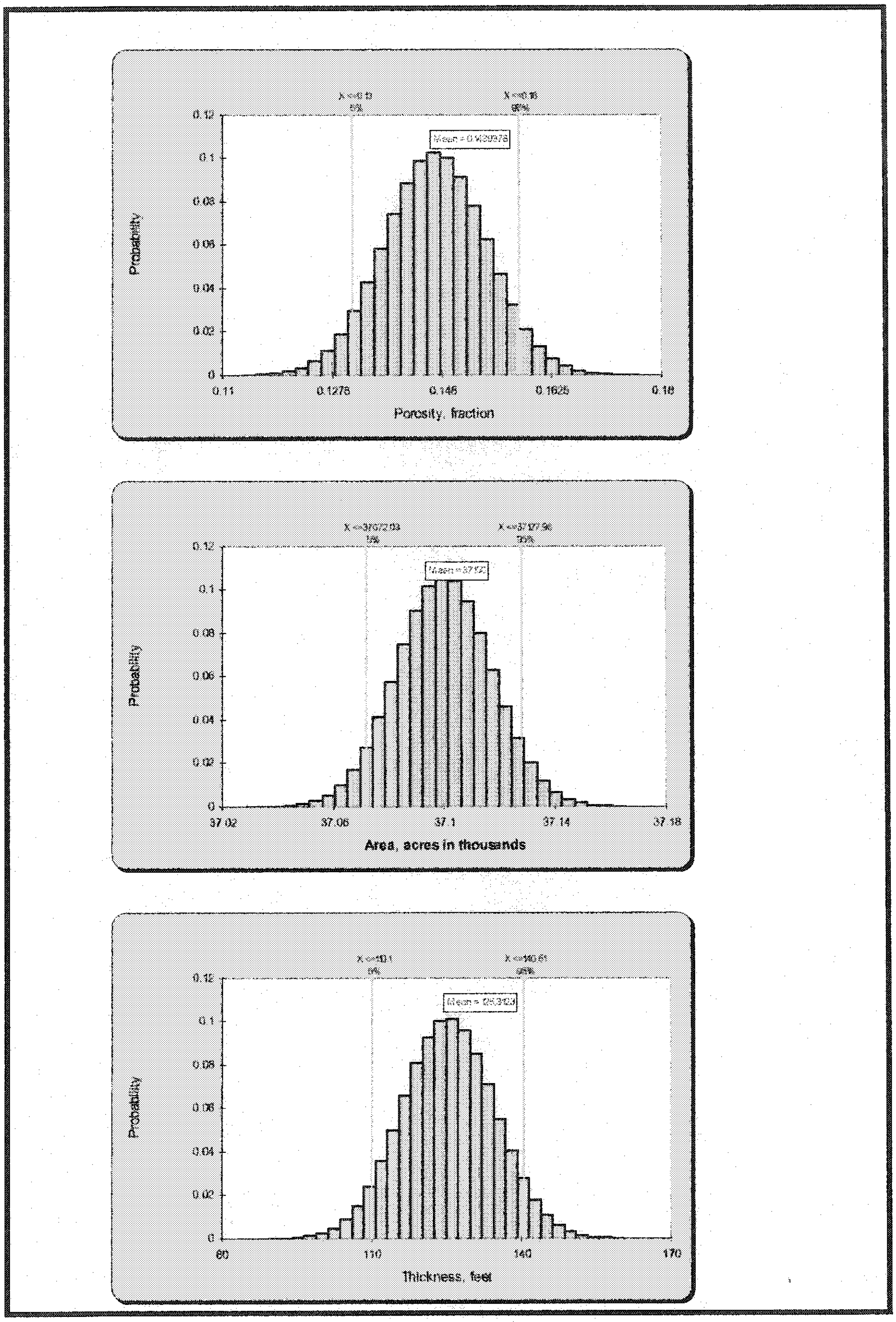


Figure 4.23: Input distribution for thickness, area, and porosity of Arab-D.

4.4.3 Dependency among Variables

The dependency or correlation between variables is essential for proper Monte Carlo Simulation to prevent overestimating or underestimating the uncertainty (Garb 1998, Murtha 1994).

A dependent parameter is one that depends in some way on the values of other parameters in the model under consideration. It is extremely important to correctly recognize correlations between parameters. The Corrmat function in @RISK is used to identify correlated parameters. In one form, the value of an uncertain dependent variable can be approximately calculated from an equation as a function of other uncertain model variables. Tables 4.6 to 4.9 show the matrices of correlation coefficients between porosity and thickness for zone-1, zone-2, zone-3, and Arab-D as one unit. Correlation is a quantitative measurement of the strength of a relationship between two variables. The correlation value can vary between -1 and 1. A value of 0 indicates there is no correlation between variables; they are independent. A value of 1 indicates a complete positive correlation between the two variables. A value of -1 indicates a complete inverse correlation between the two variables (Murtha, 2002).

Matrix1 (2x2)	zone1 Porosity	zone1 Thickness
zone1 Porosity	1	-0.002
zone1 Thickness	-0.002	1

Table 4.6: Correlation matrix using original data for Zone-1 of Arab-D Reservoir.

Matrix2 (2x2)	zone2 Thickness	zone2 Porosity
zone2 Thickness	1	0.006
zone2 Porosity	0.006	1

Table 4.7: Correlation matrix using original data for Zone-2 of Arab-D Reservoir.

Matrix (2x2)	zone3 Thickness	zone3 Porosity
zone3 Thickness	1	-0.06
zone3 Porosity	-0.06	1

Table 4.8: Correlation matrix using original data for Zone-3 of Arab-D Reservoir.

Matrix Total (2x2)	Total Porosity	Total Thickness
Total Porosity	1	-0.25
Total Thickness	-0.25	1

Table 4.9: Correlation matrix using original data for Arab-D.

The field data cross plots are a good method of identifying dependency. If actual data for two parameters are plotted against each other and a trend is noticed, then a correlation exists between the parameters. In this study, net pay thickness and porosity displayed a weak negative correlation in zone-1 (Figure 4.24), but weak positive correlations in zone-2 (Figure 4.25) may be due to local sedimentary-diagenetic facies. The variance of zone-1 is (R^2=0.51) whereas variance of zone-2 is (R^2=0.35).

In literature there are many examples both for positive and negative correlations of net pay and average porosity (Holtz, 1993). The reasons of positive or negative correlations of these parameters are porosity-depth trends, may be due to local sedimentary-diagenetic facies.

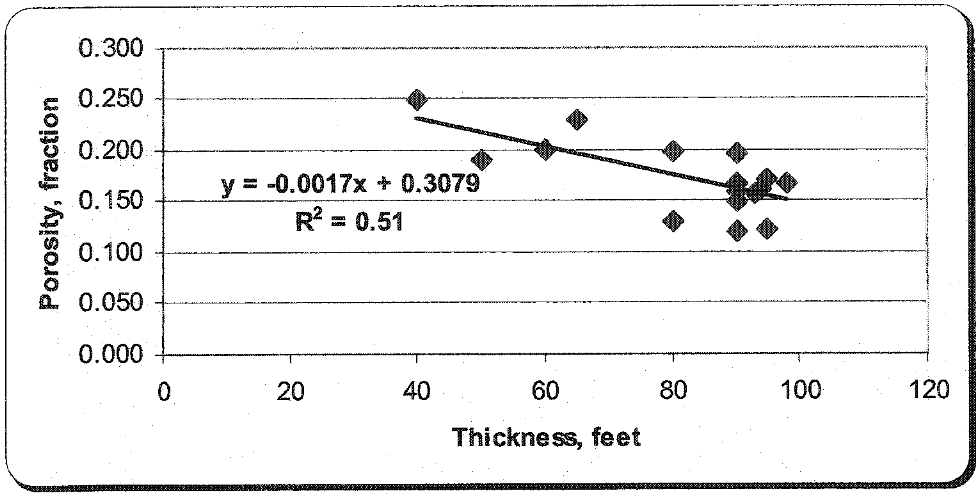


Figure 4.24: Cross plot of Porosity vs. thickness for zone-1 of Arab-D Reservoir.

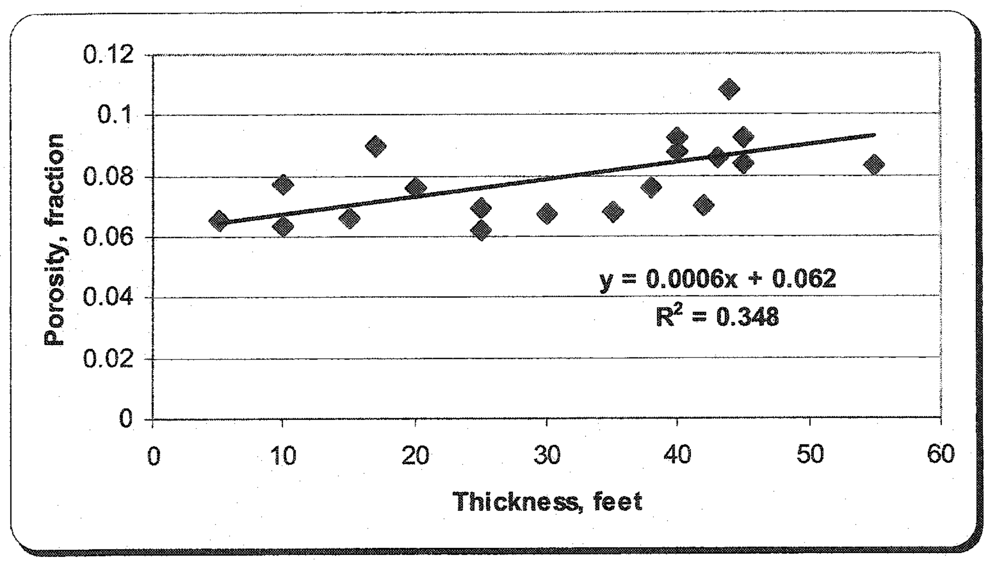


Figure 4.25: Cross plot of Porosity vs. thickness for zone-2 of Arab-D Reservoir.

4.4.4 Running Simulation

The uncertain parameters are pore-volume ($V_p = 7758\ A\ h\phi$), porosity (ϕ), net pay (h), and area (A). The mean and standard deviation for each of these variables are presented in Table 4.5. Assuming all variables are normally distributed, then our objective is to estimate total pore-volume, V_p. Monte-Carlo Simulation was run for 10,000 trials to compute the statistical data and the cumulative distribution of V_p for the dependent and independent variables.

4.4.5 Pore-volume Results from Monte Carlo Simulation

Graphical plots are the standard outputs from Monte Carlo simulations analysis. The default graphical presentation is usually a Frequency Distribution histogram. Two strategies were used in pore-volume evaluation. In one case, the reservoir was subdivided into three zones and their average properties were determined. Their pore-volume distributions for each zone were simulated individually and then aggregated also by using simulation. In second case no zonation was done and average properties were determined. The pore-volume distribution was simulated for the whole reservoir. The results of pore-volume are presented in Table 4.10 and in Figures 4.26 through 4.28 for each zone of Arab-D reservoir. They are defined on basis of the probability of hydrocarbon pore-volume (HCPV) being less than or equal to 5 percent and 95 percent, respectively. The median is defined on the basis that the probability of HCPV should be equal to 50 percent.

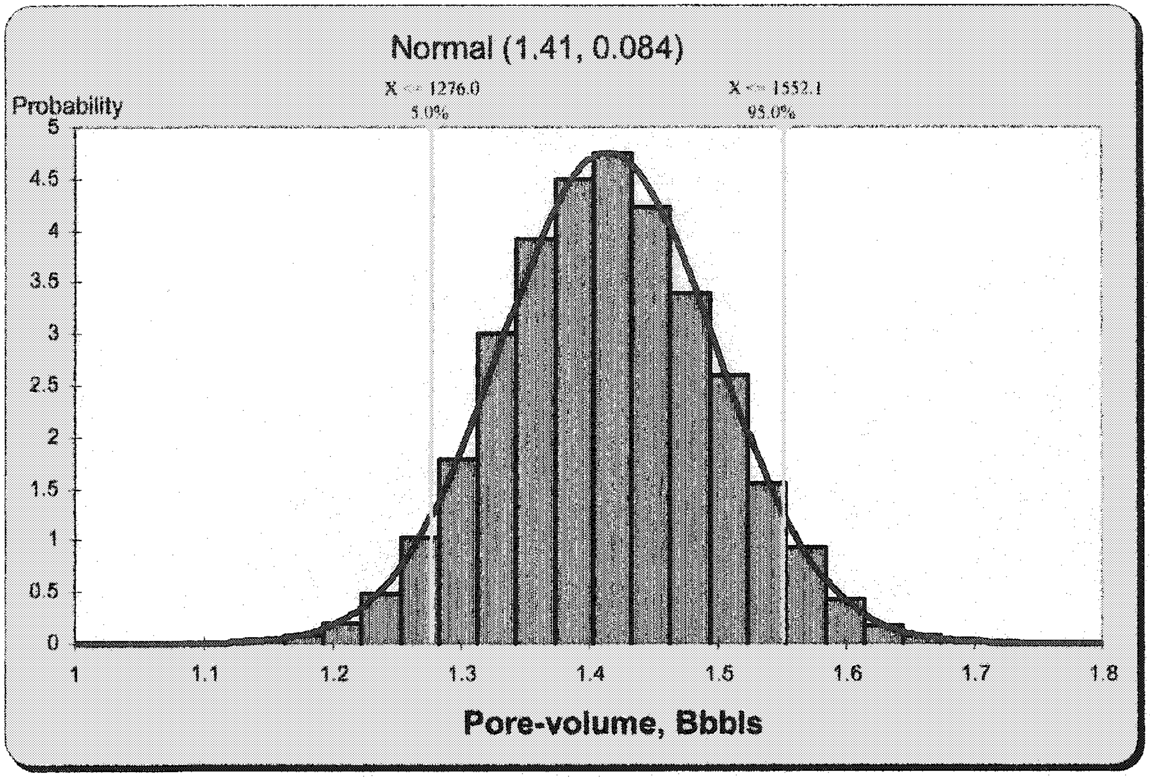


Figure 4.26 - Histogram of Simulation zone-1 of Arab-D Reservoir.

The histogram in Figure 4.29 shows the total pore-volume distribution in the reservoir with dependent parameters by applying the correlation between variables. A more useful way of viewing and presenting simulation results is the cumulative probability distribution graph. The cumulative distribution in Figure 4.30 shows the probability for the pore-volume with dependent parameters being less than or equal to the numbers on the horizontal axis.

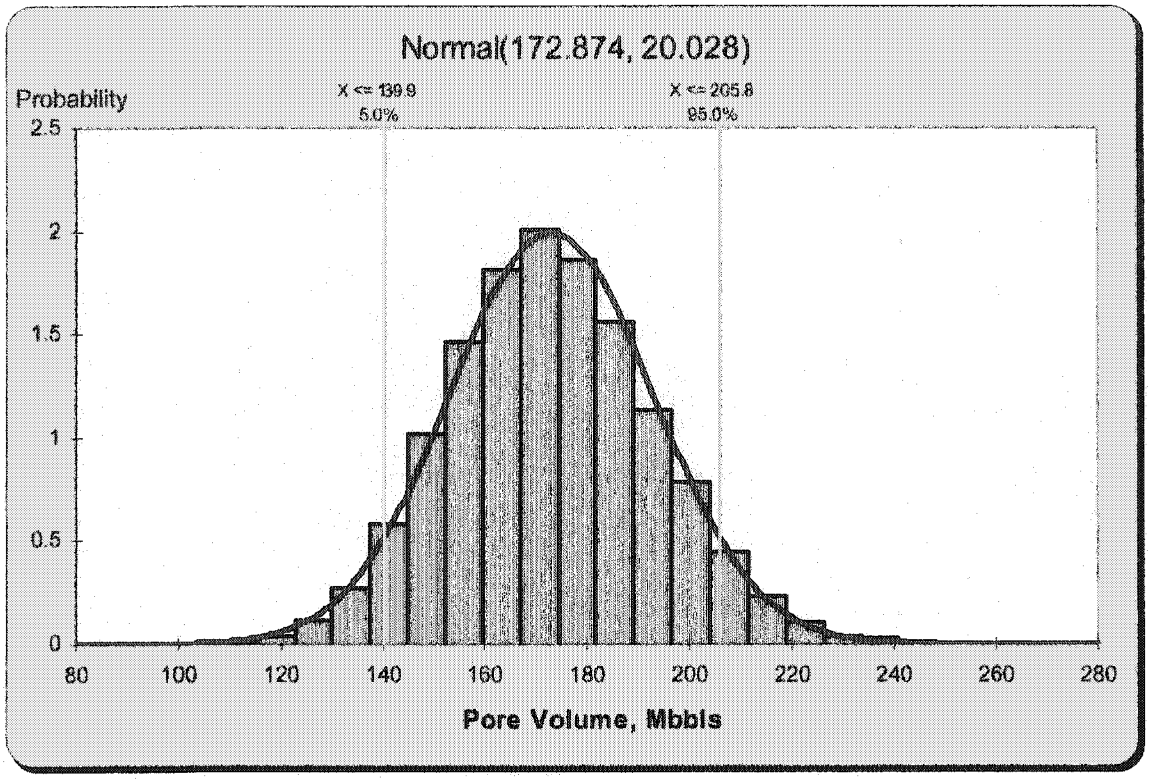


Figure 4.27 - Histogram of Simulation zone-2 of Arab-D Reservoir.

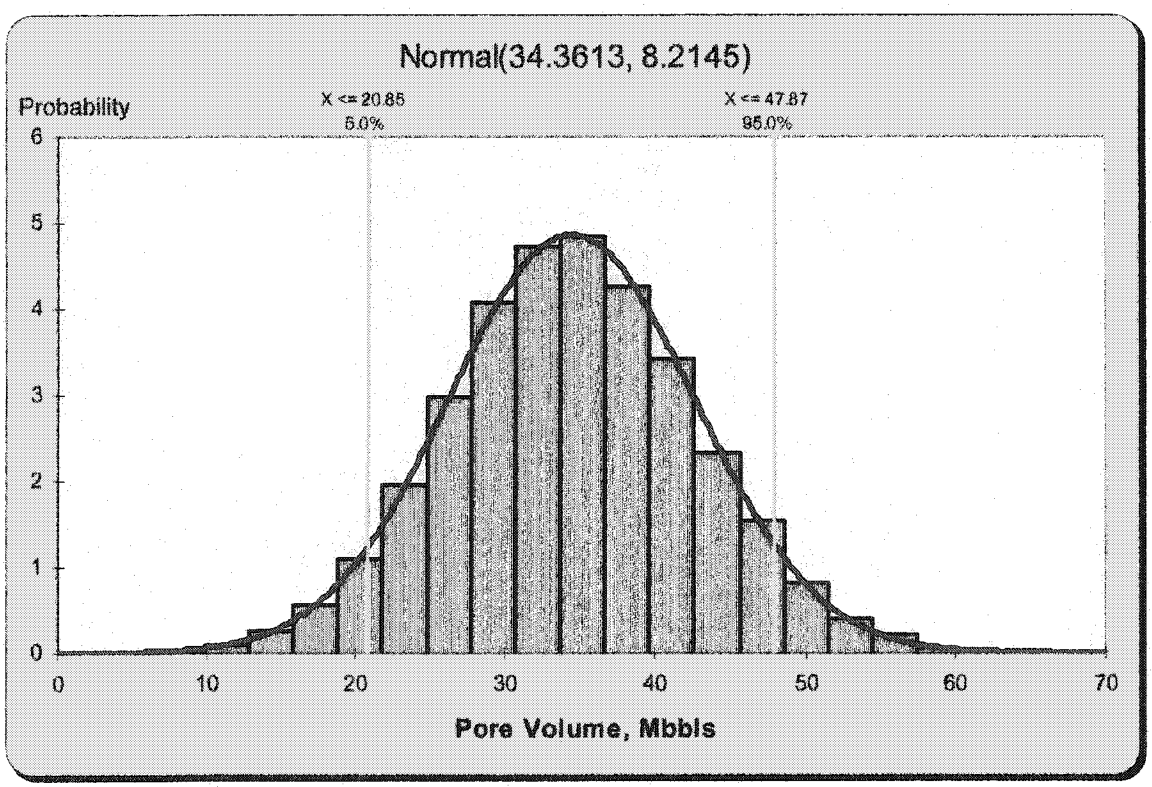


Figure 4.28 - Histogram of Simulation zone-3 of Arab-D Reservoir.

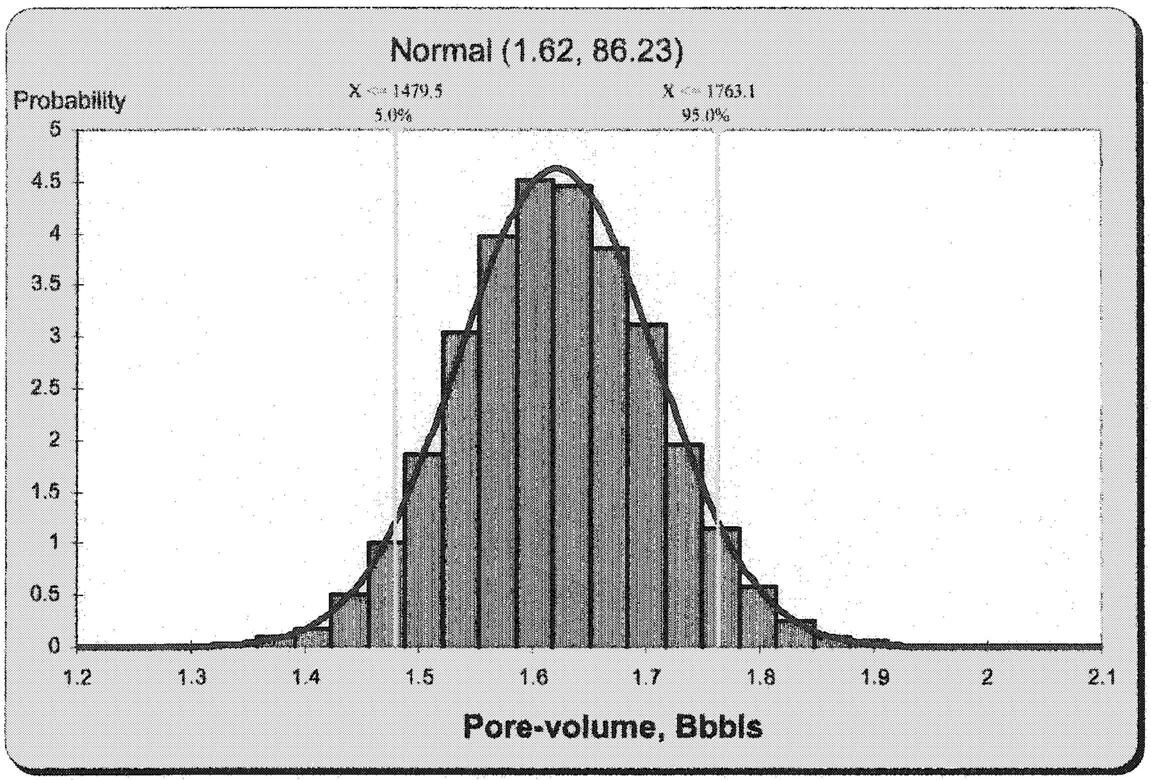


Figure 4.29: Histogram of Simulation Aggregation with dependent variables.

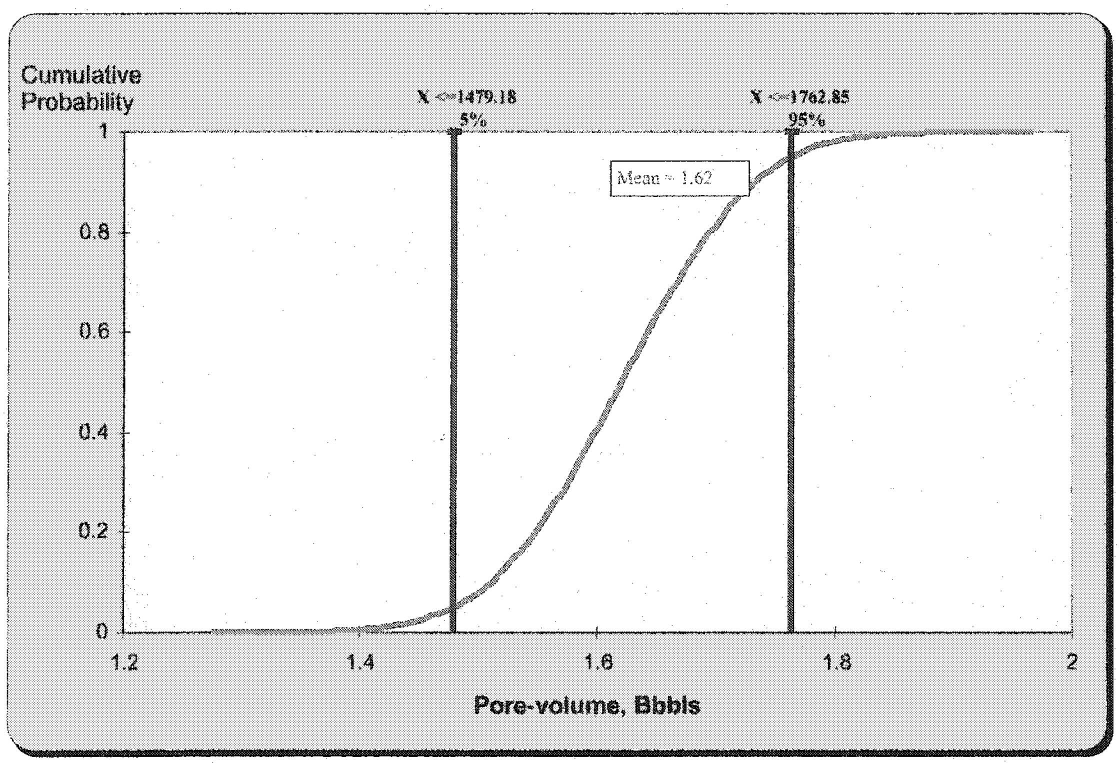


Figure 4.30: Cumulative distribution of Simulation Aggregation with dependent variables.

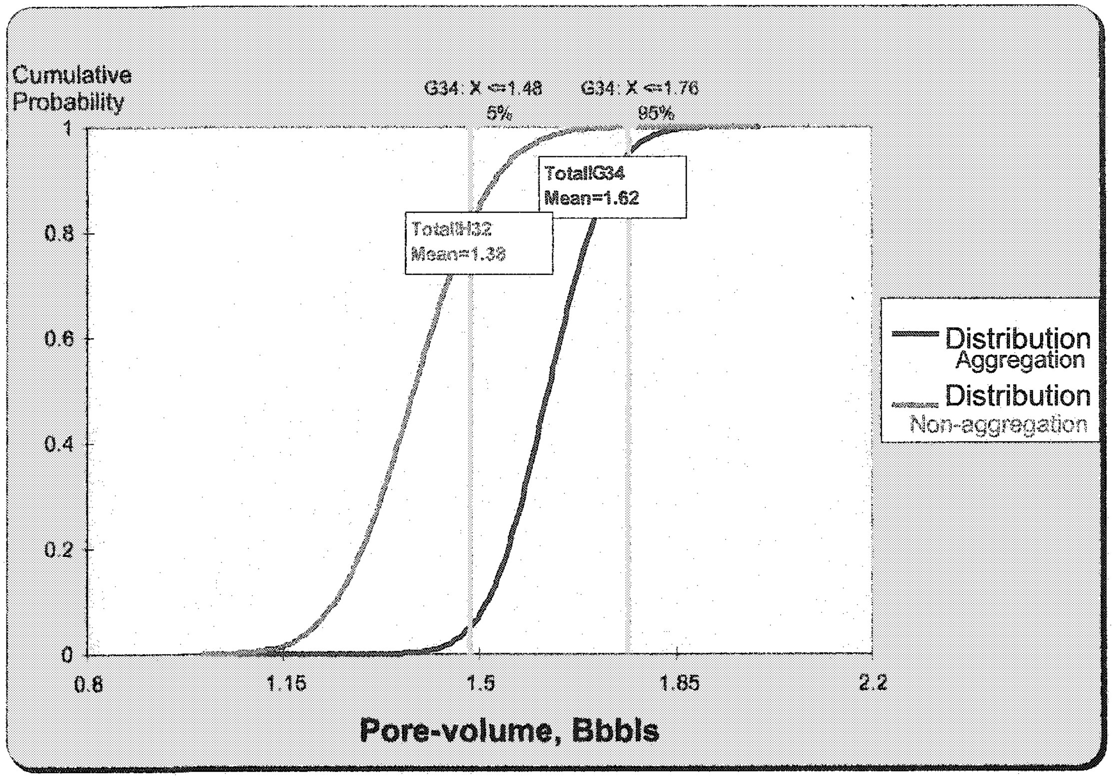


Figure 4.31 Outputs from Simulation plotted as cumulative distribution for aggregation (dependent) vs. non-aggregation case.

A statistical summary of data generated by simulation is shown in Table 4.10. The table includes values for basic statistical measures as well as the values for the range of outcomes, and other information about specific points in the range of the three zones. Table 4.11 is a statistical output from simulation that compares the case of the aggregation of the three zones and the case of all reservoir zones combined as a group. It indicates that the aggregation case showed higher hydrocarbon volume due to honoring the individual zone distributions (Figure 4.31).

Table 4.10: Statistical output data (Pore-volume) from simulation.

Outputs Worksheet	Vp (MMbbls) Zone-1	Vp (MMbbls) Zone-2	Vp (MMbbls) Zone-3
Minimum	1085.28	106.55	3.61
Maximum	1744.57	251.34	68.74
Mean	1414.02	172.86	34.37
Standard Deviation	83.23	19.91	8.22
Variance	6927.57	396.42	67.60
Skewness	0.03	0.150	0.029
Kurtosis	3.04	3.0	3.01
Number of Errors	0	0	0
Mode	1269.06	150.65	27.38
5%	1276.72	141.15	20.82
10%	1307.91	147.52	23.86
15%	1328.09	152.21	25.90
20%	1344.84	156.00	27.42
25%	1358.54	159.06	28.77
30%	1370.48	162.08	30.03
35%	1382.33	164.75	31.17
40%	1392.76	167.33	32.23
45%	1403.72	169.77	33.30
50%	1413.41	172.34	34.33
55%	1423.86	174.93	35.33
60%	1434.40	177.41	36.38
65%	1444.85	179.96	37.45
70%	1456.34	182.98	38.65
75%	1468.74	185.93	39.93
80%	1483.60	189.53	41.30
85%	1499.93	193.90	42.86
90%	1520.42	198.75	44.99
95%	1552.73	206.59	47.93

Probabilistic assessment of the Arab-D pore-volume showed a normal distribution suggesting possible additions in pore-volume. The nature of the pore-volume frequency distribution is best modeled by a normal PDF as demonstrated by the kurtosis values close to the theoretical value of 3 and by the Anderson-Darling, Kolmogorov-Smirnov, Chi-square statistical tests as well by visual inspection. The best fitting normal function representing the distribution is shown in Figure 4.29.

Table 4.11: Statistical output from simulation that compares aggregation vs. non-aggregation cases.

Outputs Worksheet	Vp (Zone1, 2, & 3) Aggregation (MMbbls)	Vp Non-aggregation (MMbbls)
Minimum	1280.68	985.87
Maximum	1961.19	1856.70
Mean	1621.24	1383.03
Standard Deviation	86.26	112.94
Variance	7441.50	12755.51
Skewness	0.04	0.08
Kurtosis	2.99	3.05
Number of Errors	0	0
Mode	1564.87	1229.07
5%	1478.86	1197.73
10%	1510.45	1239.14
15%	1531.99	1265.70
20%	1549.20	1286.63
25%	1563.36	1307.17
30%	1575.82	1324.48
35%	1588.10	1338.90
40%	1599.73	1353.20
45%	1610.69	1368.42
50%	1620.83	1381.96
55%	1631.11	1395.94
60%	1641.57	1410.36
65%	1652.88	1425.19
70%	1664.86	1439.94
75%	1678.72	1456.94
80%	1693.56	1476.60
85%	1710.78	1499.68
90%	1732.68	1528.74
95%	1763.84	1573.27

Probabilistic assessment verifies that the 3-D geocellular model pore-volume results are good representations of the expected mean volumes. Geocellular model results are virtually identical to the mean values derived from stochastic simulation. Because of the pore-volume distribution, the mean pore-volume is a conservative estimate; therefore, the 3-D geocellular model pore-volume can also be considered conservative. The mode is nearly 5 percent larger than the mean, displaying a strong probability of larger volumes and quantifying the additions of the 3D model. The explanation for the impact of dependent sampling is straightforward.

In the dependent case, whenever a large value of area is sampled, the tendency goes for large values of net pay, porosity, and area. The resulting pore-volume is relatively large. Similarly, when a small value of area is sampled, then the other parameters excluding porosity would be small and a small value of pore-volume is expected. This magnification of extremes accounts for the larger spread of the pore-volume values for the dependent case. A comparison of output distribution from simulation dependent vs. independent inputs is shown in Figure 4.32.

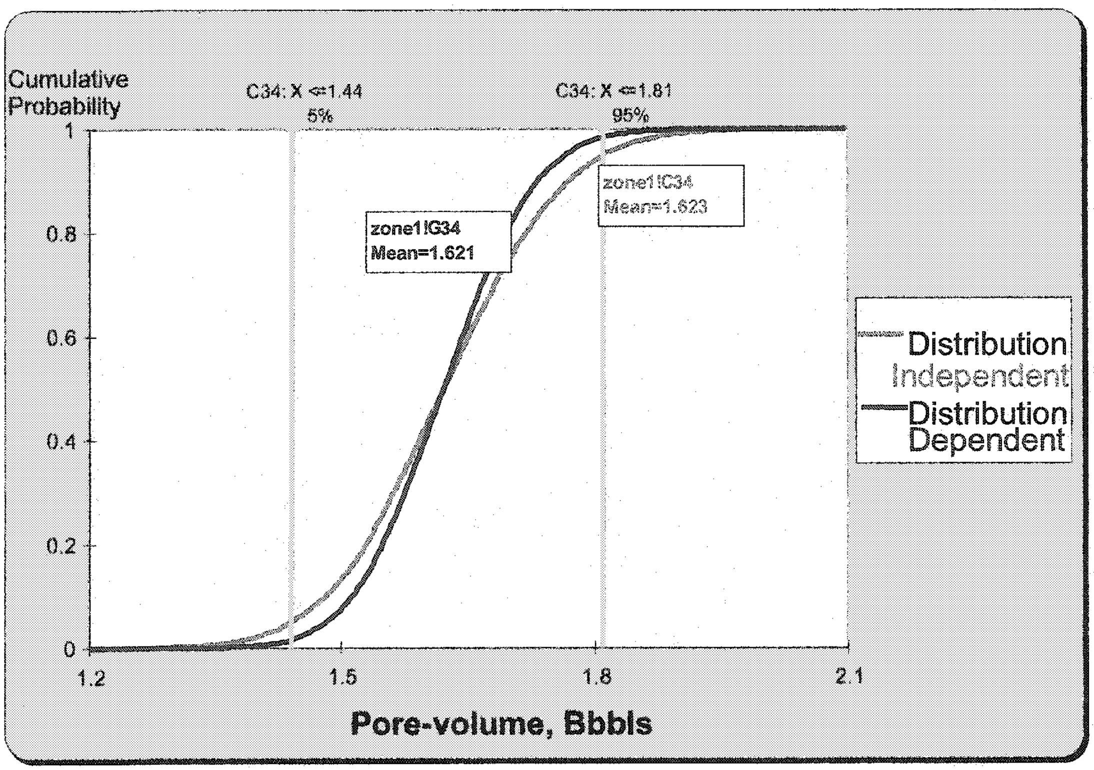


Figure 4.32: Outputs from simulation plotted as cumulative distribution for dependent vs. independent inputs.

Confidence Interval

Important information in simulation reports is that the results are expressed as ranges. The range is the simplest measure of the dispersion in a population. The minimum and maximum values of the population establish 100% interval of all possible values of the simulation. Most simulation software apply the data points in 5 or 10 percent ranges through the population, and present a confidence interval for the results.

The simulation results using Monte Carlo analysis allow the quality of the estimate to be determined. The estimate would meet the specified quality requirements if the expected accuracy ranges are achieved. This can be determined by selecting the values at the 5% and 95% points of the distribution, and calculating the percentages from the base estimate. The 5% and 95% points of the distribution establish a 90% confidence interval, and are generally expressed in percentages (Figure 4.33).

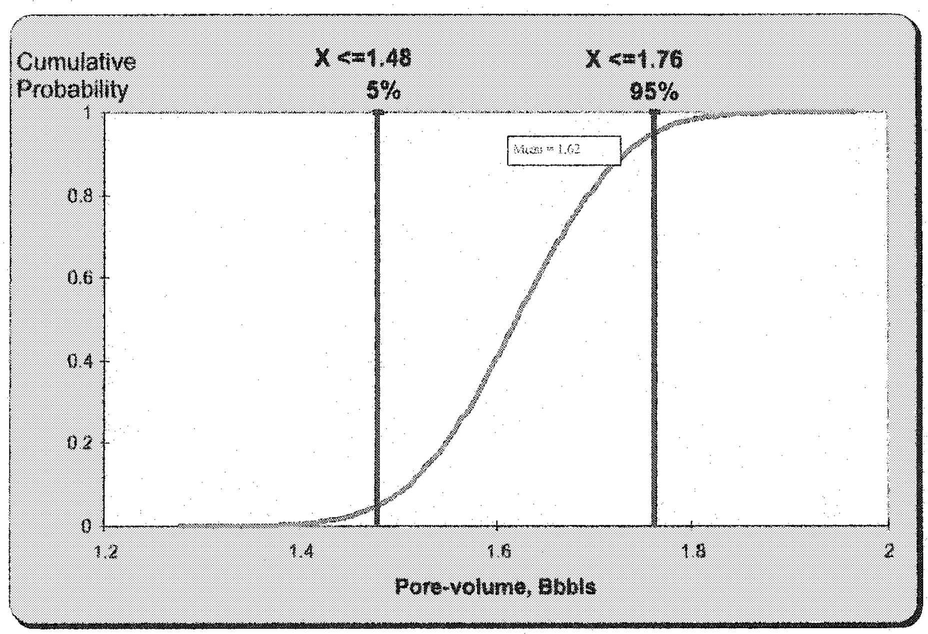


Figure 4.33: Cumulative distribution presentation of simulation pore-volume aggregation with dependent variables.

Sensitivity Analysis

Sensitivity analysis of the model determines which inputs are most significant. The software calculates sensitivities based upon either of two analytical techniques: regression or correlation. With regression analysis, sampled input variable values are regressed against output values, leading to a measurement of sensitivity by input variable. With correlation analysis, correlation coefficients are calculated between the output values and each set of sampled input values. In this case, both techniques gave similar results. The resulting "tornado" graphs (Figures 4.34 and 4.35) identify and rank the inputs. The most significant inputs are identified with longer bars at the top of the graph. The highest value belongs to the input with the largest influence on the population of outcomes of the simulation.

Sensitivity analysis of the inputs to a simulation allows reviewing estimates by concentrating on specific inputs which are most likely to improve the accuracy of the estimate. Sensitivity analysis provides the most promising opportunities to perform additional work, thus allowing these input distributions to be narrowed and the total estimate accuracy improved.

From the Tornado Correlation Graph in Figure 4.34, it is evident that porosity in zone-1 being most highly correlated with pore-volume. Next is the net pay in zone-2, while the rest parameters of the random cells in the spreadsheet do not matter much.

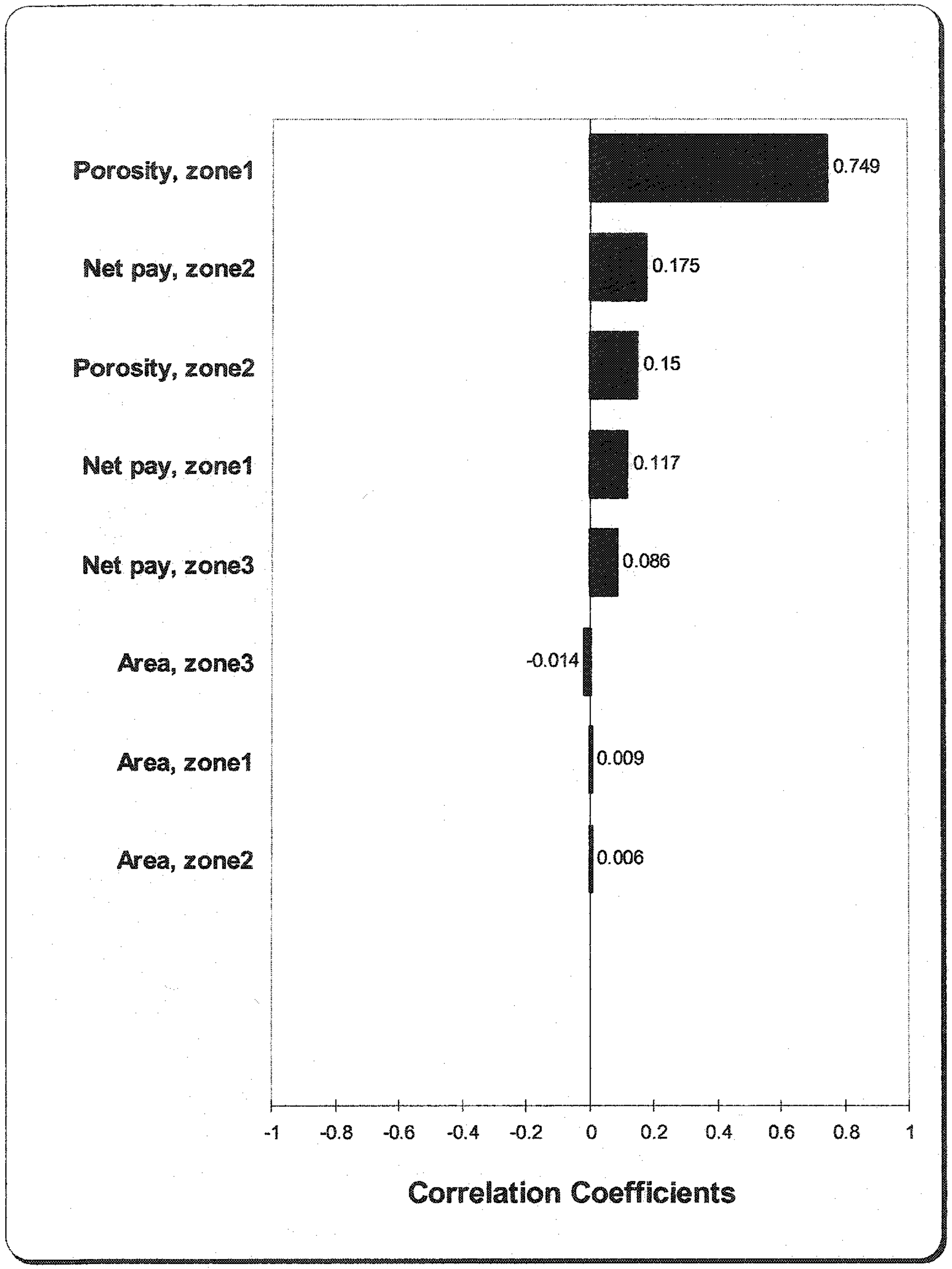


Figure 4.34: Tornado graph for the correlation coefficient of the Arab-D reservoir zones.

The Regression Tornado Graph (Figure 4.35) indicates that one standard deviation increase in porosity in zone-1 increases the pore volume by 1.12 standard deviation. A one standard deviation increase in net pay in zone-1 increases the pore volume by 0.693 standard deviation.

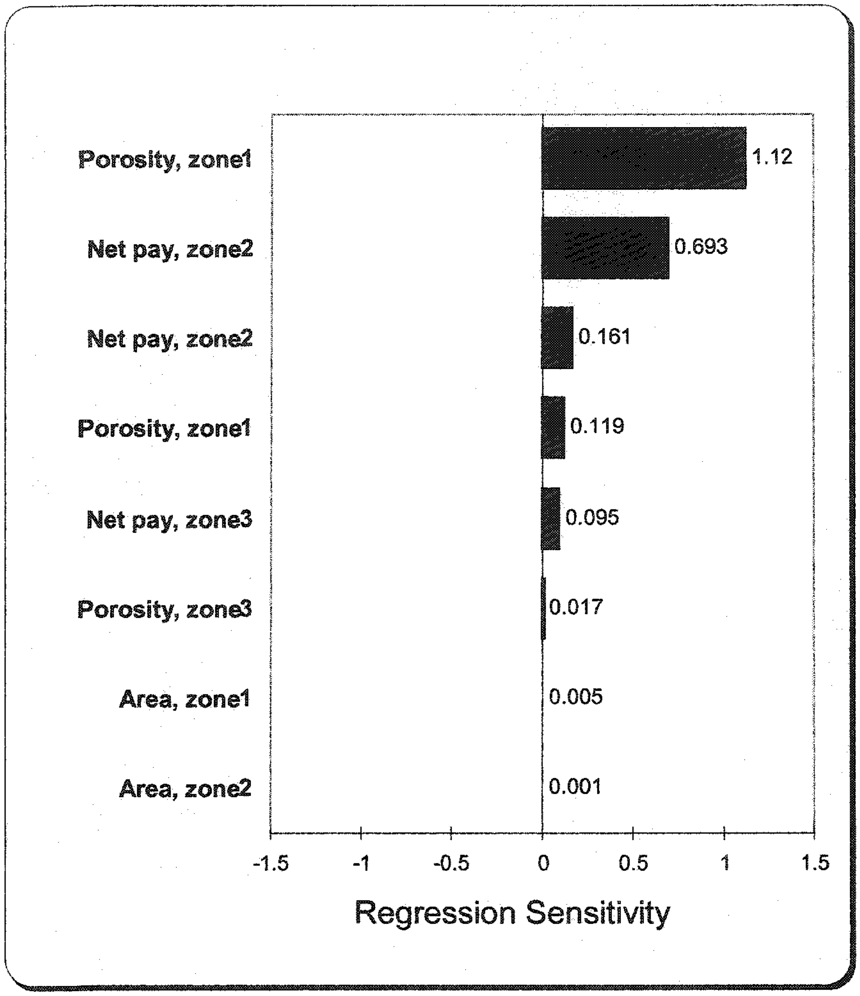


Figure 4.35: Regression Tornado graph for the Arab-D reservoir zones.

The dependent variable is the output cell (V_p) and the independent variables are each "random" @RISK functions in the spreadsheet. The final analysis suggests that the pore-volume is heavily dependent on the porosity and on the net pay thickness of zone-1 (Figure 4.35). The other zones provide small contribution to the total pore-volume.

CHAPTER 5

Conclusions and Recommendations

5.1 Summary

In a field study, several reservoir parameters, such as area, pay thickness, and porosity, were statistically analyzed both for their types of distributions and for correlation that affect the estimation of oil pore-volume and reserves. The statistical analyses were based on geological and petrophysical properties, which would help in expediting the modeling work. Deterministic oil pore-volume estimations were calculated by generating a 3-D geological model. The porosity model was generated by the Inverse Distance algorithm using porosity logs from wells. Geological, petrophysical and engineering data such as fluid description are reviewed and analyzed statistically to ascertain appropriate distribution functions.

Mapping the hydrocarbon reservoir was the most important step in volumetric estimation. Cross sections and diagrams were prepared to understand pool geometry. A series of maps including structural maps, isopach maps, and porosity-thickness maps were prepared in a sequential manner. These maps contain and integrate results of core data, well log calculations, and seismic data. When field data are available, it can be used to generate input distributions for a Monte Carlo simulation. The first step is to group the data and construct a histogram and a cumulative distribution function. Spreadsheet add-in software can accommodate these general shaped distributions as well as common theoretical distributions. Latest software has advanced options to fit special distribution functions to data distributions.

The field data can also be used to test for dependency between pairs of parameters by making crossplots to identify relationships. When two or more parameters in the underlying model appear to be dependent, their degree of dependence can be measured by regression and correlation tools. Any dependency of this sort can be incorporated in the Monte Carlo simulation.

Two strategies were used in pore-volume evaluation. In one case, the reservoir was subdivided into three zones and their average properties were determined. Their pore-volume distributions for each zone were simulated individually and then aggregated also by using simulation. In second case no zonation was done and average properties were determined. The pore-volume distribution was simulated for the whole reservoir. Parameters in a model can be either "independent" or "dependent" and both cases were assumed in this study. Applying aggregation and dependency lead to better results by having additional pore volume. Hydrocarbon volumes calculated in both cases were significantly different.

In one case the geological parameters were considered to be mutually independent while in the other they were correlated. Monte Carlo simulations were run on both cases. In the case where geological parameters were correlated, simulation resulted in a tighter hydrocarbon volume distribution (smaller standard deviation).

A simulation incorporating the empirically found distributions revealed that the range of the output parameter, pore-volume, was affected by the decision of including dependence relationships.

The deterministically derived pore-volume from the 3D model closely matches the mean pore-volume of the Monte Carlo simulation model. The 3D geocellular model represents the actual geology. The Monte Carlo simulation results came very close to the 3D model, suggesting that the parameter distributions used in Monte Carlo simulation were truly representative of the geology.

The appropriate probability functions within typical Monte Carlo simulators are reviewed, and the input parameters carefully screened for the field. In addition, the probabilistic method is applied to the hydrocarbons pore-volume calculation using the output from simulation runs which test critical reservoir parameters. In the case of the Arab-D reservoir, total pore-volume probability distributions are shown to be best modeled by a normal density function.

5.2 Conclusions

Based on this study, the main conclusions are as follows:

1. Monte Carlo simulations are valid only when the input parameter distributions are representative. Comprehensive statistical analyses are very important to model representative parameter distributions. Sufficient time should be spent on them because these analyses would have a big impact on the accuracy of the model.
2. Integrating deterministic and probabilistic modeling improves the overall model accuracy and leads to better decisions.
3. Data integration has a big impact on the results.
4. The results contain maximum information about possible outcomes compared with both the probabilistic and deterministic approaches.
5. Simulation results closely matched deterministic pore-volume and suggest that the parameters were modeled correctly.
6. Sensitivity analyses indicate that the porosity of zone-1 of Arab-D reservoir has the maximum influence on results.
7. Applying aggregation and dependency lead to better results by having additional pore volume.
8. The advantages of Monte Carlo simulation are: correlations and inter-dependencies related to gross rock volume can be more properly modeled, incorporation of more realistic gross rock volume distributions, more direct use of seismic and geological information, and easier evaluation of sensitivities of individual parameters.

9. Since Arab-D reservoir oil pore-volume and its associated uncertainty have been quantified in this study, oil-in-place and oil reserves can also be better quantified using these results.
10. The Monte Carlo method is straightforward to apply and it provides excellent estimates of pore-volume.
11. Monte Carlo Simulation was successfully applied to a real oil field to determine the distribution of basic reservoir characteristics (net thickness of oil sand and averaged porosity).
12. In applying Monte Carlo Simulation method, the pore-volume estimation may be obtained considering the heterogeneity of the reservoir.
13. Distributions provide a better representation of the type of uncertainty commonly encountered in oil pore-volume estimation. Furthermore, they require certain data relevant to porosity, net pay, and area. These advantages allow distributions to be applied in many situations where uncertainty would have previously been ignored or unrecognized.

5.3 Recommendations

Based on this study, the followings are recommended:

1. 3D seismic data helps to better interpolate petrophysical parameters at well locations and reduces uncertainty. Both Monte Carlo simulations and deterministic 3D models can be made more representative using 3D seismic. Therefore, it is highly recommended to run 3D seismic surveys in the early field development stage when wells are still widely spaced. The seismic data will help in improving the accuracy of porosity models and in locating new wells.
2. A probabilistic analysis improves our understanding of the uncertainty and how to quantify it. Therefore, it is advisable to encourage the use of probabilistic tools because they (a) better capture expert judgments; (b) better characterize uncertainty; and (c) provide more accurate quantitative results.
3. Porosity models can be improved by integrating logs, cores, and thin-sections at well locations. The calculated porosity from logs has to match overburden corrected core porosities. It is recommended to conduct good integrated petrophysics program to quantify porosity and the geological controls on porosity.
4. Integrated deterministic and probabilistic methods should be used in other fields/reservoirs to calculate pore-volume (and oil-in-place, oil reserves).

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VITAE

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